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Dynamics of Investment and Firm Performance: Comparative evidence from manufacturing industries.*

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Abstract

This paper investigates the channels linking investment and firm performance in the French and Italian manufacturing industries and proposes a novel methodology to identify investment spikes which corrects for non-linear size dependence. Using large datasets reporting observed investment from official sources, we provide a systematic comparison of the relation between investment and firm performance across i) different definitions of investment spikes, our proposed measure and previous ones; ii) different institutional settings, i.e. France and Italy; iii) several performance proxies; and iv) investment types. We show that the failure to account for the scaling relation between investment spikes and firm size can bias such analyses. Moreover, differences also emerge across countries in the way investment spikes translate into future firm performance.

JEL codes: C14, D22, D24, D92, E22, L11, L23, L60

Keywords: Firm heterogeneity, investment spike, industrial dynamics, corporate performance, capital accumulation, technical change.

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1 Introduction

In this paper we investigate the relation between firms' investments in tangible assets, and corporate performance. Assessing the impact of investment at the level of the firm has not always been a viable research topic because, for many years, it was hindered by lack of observed investment data. It is only recently that scholars have started to document the nature of firms' investment behaviour. One of the first attempts was by Doms and Dunne (1998) who used data on U.S. plants and firms. This seminal paper has inspired a growing body of work reporting similar results for other countries and industries.[1] A common finding of these studies is the lumpy nature of firm-level investment: years of inactivity or repair and maintenance are followed by one or several years of heavy investment - with respect to both the firm and the industry as a whole. For instance, Carlsson and Laséen (2005) show that non-convex adjustment cost models provide a more appropriate framework for explaining investment decisions, and reject those that assume a smooth pattern of capital accumulation. The observed lumpiness of investment rates at both plant and firm levels can also be explained more generally as due to investment irreversibility, resulting from the idiosyncratic nature of the capital purchase and the indivisibility of physical capital.

The interrelation between heterogeneous firm-level patterns and aggregate dynamics is rather complex. The empirical evidence suggests that most of the variation in aggregate investment can be explained by changes in the number of establishments undergoing such large investment episodes, those "investment spikes" being procyclical (Cooper et al., 1999; Gourio and Kashyap, 2007).[2] Moreover, if at the macroeconomic level the relation between equipment investment and economic growth is well established in the literature (De Long and Summers, 1991), the evidence is much more scant for the impact of firm-level investment on the ability of firms to grow or to increase efficiency. This is important because aggregate labour productivity growth is largely driven by within-firm changes (Baily et al., 1992; Foster et al., 2001; OECD, 2001). Thus, it is apparent that in order to interpret changes in aggregate investment and also how those changes relate to economic growth, one needs a thorough understanding of the heterogeneous behaviour occurring at firm level. It is on this area that we focus in this paper.

An empirical stream of literature investigates the relationship between capital adjustment episodes and a number of firm-level characteristics, using different methods to identify the investment spikes and different datasets (see among the many others Power, 1998; Sakellaris, 2004; Nilsen et al., 2009). What these contributions have in common is the view that such spikes are abnormal events with respect to an expected level of the ratio between investment and the stock of capital. Because these events are rare at the firm level, such "shocks" are expected to be associated to significant changes in firms' performance before and after the spike. In this respect, they represent yet another channel through which persistent heterogeneous performance across firms in each industry is sustained (Bartelsman and Doms, 2000; Syverson, 2011).

The theoretical framework to which we resort to study the impact of investment spikes on the various performance proxies is provided by the literature on embodied technical change (Cooley et al., 1997; Jensen et al., 2001), whereby investments in new machinery bring about technological upgrading, because new capital embodies more recent technology. Hence, following an investment episode we should observe a productivity increase, which in turn translates into market share gains, thus sales and employment growth. Still, following the "learning-by-doing" argument (Jovanovic and Nyarko, 1996), these medium-to-long-run positive productivity effects might be anticipated by short-run costs. The empirical literature on the subject (Power, 1998; Huggett and Ospina, 2001; Sakellaris, 2004; Shima, 2010) has only partially confirmed these theoretical conjectures. If it reports that the effect of investment spikes on productivity growth is negative in the short run, studies evaluating long run

[1]Among the papers using a comparable methodology to Doms and Dunne (1998), the reader could refer to Duhautois and Jamet (2001) for France, Nilsen and Schiantarelli (2003) and Nilsen et al. (2009) for Norway and Carlsson and Laséen (2005) for Sweden.

[2]The impact of lumpy investment patterns on aggregate outcomes have also been studied in macroeconomic models, firms' behaviours either being driven by non convex capital adjustment costs (Thomas, 2002; Christiano et al., 2005; Fiori, 2012; Bachmann et al., 2013) or adaptive routines (Dosi et al., 2006). In the latter case, firms do not try to catch up with an optimal level of capital but respond to expectations of significant demand growth.

impacts fail to report a positive relation between investment lumps and productivity growth. Besides, the type of investment can affect the outcome at firm level. Replacing obsolete machinery with modern equipment that uses more up-to-date technologies is more likely to result in increased productivity than pure "expansionary" investment which does not involve technological upgrading, for example, setting up an additional plant to increase production capacity. In this respect, Licandro et al. (2004) report a positive effect of investment spikes on productivity but it is limited to the sub-group of innovative firms.

Besides productivity[3] and its growth rate (Power, 1998; Bessen, 1999; Huggett and Ospina, 2001; Nilsen et al., 2009; Shima, 2010), the performance proxies under consideration in these studies include employment growth (Asphjell et al., forthcoming), sales growth (Licandro et al., 2004) or other factors of production (Sakellaris, 2004; Nilsen et al., 2009).

The present paper contributes to this stream of literature as follows. First, it provides the first large-scale evidence on the patterns of firm-level investment and their relation to firm performance, for Italy and France.[4] If most research on the topic has relied on U.S. data (see, in between others Doms and Dunne, 1998; Power, 1998; Cooper et al., 1999; Sakellaris, 2004) a few studies have addressed similar research questions related to French or Italian firms. However, they either rely on surveys to obtain actual investment data, which limits the scale of their analysis (Parisi et al., 2006 for Italy) or they rely on investment data computed as the (adjusted) difference in capital stock over two consecutive years (Bontempi et al., 2004; Del Boca et al., 2008 for Italy and Mairesse et al., 1999; Bond et al., 2003 for France).

The second contribution of our paper consists in the presentation of a novel methodology to identify abnormal investment events of firms, which the literature calls investment spikes. In accordance to previous studies (Power, 1998; Cooper et al., 1999; Nilsen et al., 2009), we identify investment spikes by defining a threshold level above which an investment rate is revealing of a relevant episode of capital adjustment, hence an investment that is not related to the routine activities of annual repair and maintenance. In addition, we also respond to characterizations of such measures as being "ad hoc" (Letterie and Pfann, 2007), not driven by the data, by adapting the lumpiness threshold to the non-linear empirical relation between firm size and investment rate for each sector-year couple.

Employing this definition of a spike, we investigate which firm characteristics make an investment project more likely to take place, and relatedly, how an investment episode impacts on firm performance in the following periods. We compare the findings of the methodology that we propose with those of previous contributions employing different spike measures. We focus on the heterogeneity in investment patterns - *across* as well as *within* firms' time series. The former analysis indicates those characteristics that differentiate investing and non-investing firms; the latter helps understanding the factors driving the timing of the decisions, as well as the performance gains from investing. To this end we estimate the returns from investment activity on a series of performance proxies. In doing that we exploit country variation, between France and Italy, to discern those patterns that are country-specific from more general ones. In the year of investigation, France and Italy reported stark differences in performance in terms of growth of productivity in the manufacturing sector. While France displayed a growth of value added per person employed well beyond 3%, a percentage even higher than what reported by Germany (OECD, 2008, page 44), Italy registered a negative productivity growth. This paper also looks at the link between investment and productivity growth as a possible source of the difference in the performance of the two countries. Further, we can also (for France only) control for those kinds of investments which involve the opening of new plant for an existing firm.

Finally, our contribution also provides a framework for comparing the analysis of the relation between firm investment spikes and performance across i) different definitions of investment spikes, our proposed measure and previous ones; ii) different institutional settings, i.e. France and Italy; iii) several performance proxies; and iv) investment types.

The rest of the paper is organized as follows. Section 2 describes the French and Italian databases. Section 3 discusses the lumpy nature of firm-level investment, it introduces our proposed measure of

[3]Either labour productivity or total factor productivity is considered. The former is used in Power (1998), Bessen (1999), and Nilsen et al. (2009), the latter is used in Huggett and Ospina (2001) and Shima (2010).

[4]Duhautois and Jamet (2001) used observed investment from the French tax dataset (fichier des Bénéfices réels normaux, INSEE), however they do not investigate the relation between investment spikes and firm performance.

Table 1: Size distribution of firms by size class.

Size Class	France			Italy		
	1999	2002	2006	1999	2002	2006
20-49 employess	55.44%	54.31%	52.59%	31.86%	28.94%	29.27%
50-250 employees	35.92%	36.59%	37.95%	56.16%	57.89%	57.82%
250 employees or more	8.64%	9.10%	9.46%	11.98%	13.17%	12.96%
Total Number of firms	18,538	18,382	15,420	9,048	9,262	8,419

spikes and compares it to the existing ones. Section 4 analyses the determinants of the probability of observing a spike, and examines the effects of such an event on firm performance, across the four dimensions mentioned above. Section 5 concludes.

2 Data and Descriptive Statistics

The paper draws on two similar firm-level databases for France and Italy, respectively, the Enquête Annuelle d'Entreprise (EAE) and Micro.3.[5] A unique feature of these databases is that as well as reporting standard accounting information they include the value of acquisitions of tangible and intangible assets in each year.

EAE data are collected by the statistical department of the French Ministry of Industry (SESSI) and provided by the French Statistical Office (INSEE). The French sample includes longitudinal data on a very exhaustive panel of French manufacturing firms located in the national territory, for the period 1989-2007. Micro.3 is based on the census of Italian firms yearly conducted by the Italian Statistical Office (ISTAT) for the period 1989-2006. Both samples contain information on firms with more than 20 employees, classified according to their sector of principal activity. Our study focuses on the manufacturing industry, i.e. sectors 171 to 361 in the NACE rev 1.1 classification. Both Micro.3 and EAE are quite representative of the two economies, and in particular, they account for a large share of their respective manufacturing industries: 40% of employment and around 60% of value added, see Grazzi et al. (2013).[6]

In relation to the definition of the variables employed in the empirical analysis, as a proxy for firm-level investment we use acquisition of tangible fixed assets.[7] Due to small differences in the variable definitions, the Italian database reports the value of acquisitions only for machinery and equipment, while the French data includes also land and property. However, note that over the period 1989-1995 the investment variable for French firms is broken down into its main components, and in those years the share of land and property in total investment is between 14% and 18%. Notwithstanding these slight differences in the definitions of the investment variables for Italy and France, Figure 1 shows that they have comparable statistical properties and trends over time. The investment rate (Inv. rate) is the ratio of investment (flow variable) to tangible fixed assets (stock variable). In particular, we consider investment in year t in relation to the stock of tangible assets at the end of the previous year, (I_t/K_{t-1}).

[5]Both databanks were made available to the authors under the mandatory condition of censorship of individual information. The Micro.3 database was developed in a collaboration between the Italian Statistical Office (ISTAT) and members of the Laboratory of Economics and Management of Scuola Superiore Sant'Anna, Pisa. More detailed information on the development of the Micro.3 database can be found in Grazzi et al. (2013).

[6]More detail about the data can be found in the Appendix.

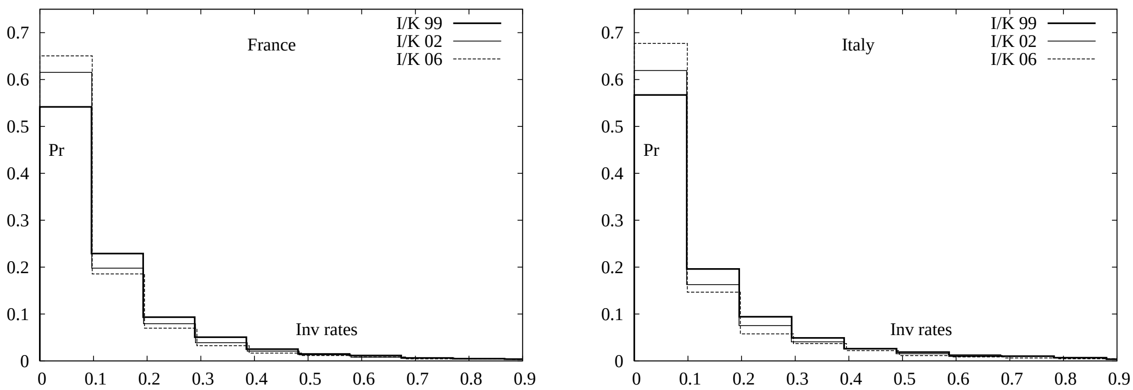
[7]We also tested whether including leased capital in the definition of the investment variable affected the results. Since it did not, we do not consider leased capital. The decision to exclude leased capital is also motivated by accounting differences between the two countries. Indeed, the variable is reported as the yearly cost of rents in the French database whereas in the Italian one it is the total indebtedness in the year of the investment.

Table 2: Means and medians (in brackets) for the sample used in the regressions.

	France			Italy		
	1999	2002	2006	1999	2002	2006
Empl	116.8 (46)	125.6 (46)	133.7 (48)	170.6 (75)	171.7 (82)	172.9 (84)
Sales	20602 (5030)	24238 (5502)	32905 (6590)	44406 (12741)	43930 (14405)	49614 (15638)
LabProd	48.10 (39.87)	48.80 (40.57)	55.99 (44.03)	53.38 (46.38)	54.04 (47.28)	54.69 (47.85)
RoS	0.066 (0.065)	0.057 (0.060)	0.057 (0.057)	0.110 (0.099)	0.098 (0.091)	0.086 (0.080)
Inv rate	0.160 (0.085)	0.136 (0.069)	0.117 (0.059)	0.159 (0.084)	0.158 (0.064)	0.137 (0.050)

Note: Sales and labour Productivity are in thousands of euro and deflated according to the production price index at the 2-digit level of industry disaggregation.

Figure 1: Histograms of investment rates in 1999, 2002 and 2006. France (left) and Italy (right).



In addition to the values of investment and capital stock, the French dataset also includes information on the number of plants for each firm. We employ this variable to complement the empirical analyses since setting up a new plant identifies episodes of investment associated with expansion and capacity building rather than replacement/repair.

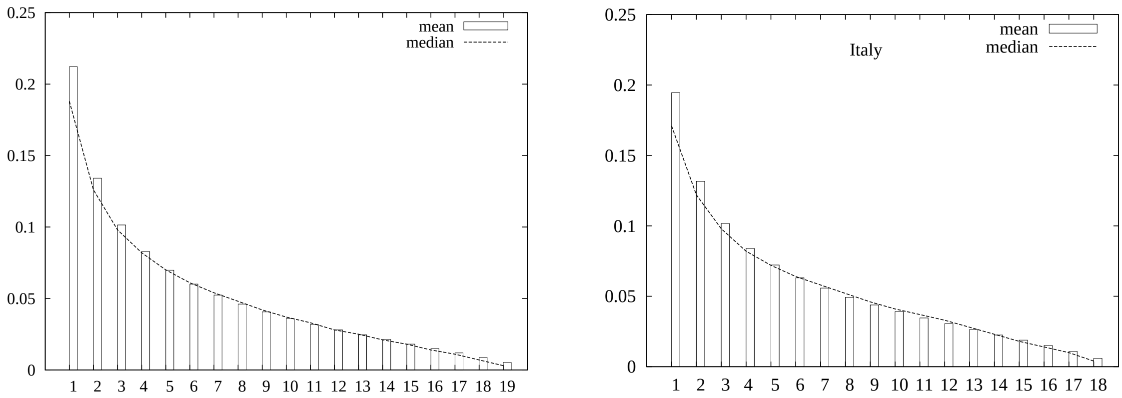
The other variables that are employed in the empirical analysis are number of employees (Empl.), labour productivity (Prod) computed as value added per worker, total sales (Sales), and return on sales (RoS) as a proxy for profitability. Note that our results using labour productivity are also robust when employing instead Total Factor Productivity (results are reported in the Appendix). RoS is defined as Gross Operating Margin[8] over total sales. This definition of profitability was chosen because it is not influenced unduly by accounting methods and it can be computed in the same way for both countries. We also consider growth rates as the logarithmic differences of these variables.

Tables 1 and 2 report some descriptive statistics for the sample employed in the econometric analysis. In particular, Table 1 shows that the Italian firm size distribution weights relatively more larger firms as compared to France.[9] This is associated with a smaller number of observations for Italy with respect to France. These differences in the firm size distributions for the two countries also generate bigger averages (and medians) for some of the variables of interest (see Table 2).

[8]Gross Operative Margin is valued added minus wages, salaries, and social insurances paid by the firm.

[9]This relates to the sample construction in more recent years, and it is further explained in the technical Appendix.

Figure 2: Investment shares by rank in France (left; from 1989 to 2007); and in Italy (right; from 1989 to 2006). Investment shares on the vertical axis; ranks on the horizontal one.



Note: The time period for Italy is 1989-2006, 18 years only.

3 Investment lumpiness and spike measures

This section investigates the patterns of firm-level investment in the French and Italian manufacturing industries. We provide evidence of lumps in investment behaviour and then compare the different methodologies proposed in the literature to identify investment spikes. Finally, we propose our own methodology for identifying "abnormal" investment events at the firm level.

Figure 1 depicts histograms of investment rates for France (left) and Italy (right) in selected years. Notice that the shape of the distribution does not change over time. From the plot it is apparent that for most firms investment rates are very low: in 1999, 55% of firms in France and 57% in Italy reported investment rates of 10% or lower. At the same time, 5% (6%) of French (Italian) firms displayed much higher investment rates of 50% or more. This points to relevant differences in the capital adjustment patterns *across firms*.

There is at least one more dimension that is revealing of the lumpy nature of investment, related to how the individual firm decides to allocate its investment over a certain period of time. Were we to observe that, on average, the profile of annual firm-level investment was rather flat, that would support the conjecture of a smooth process of capital adjustment at firm level. The reverse would be true if one were to observe spikes in firm-level patterns, because this would suggest that the firm tends to concentrate investment in a few periods. In order to provide evidence of investment lumpiness at firm level, we rank, for each company, the investment carried out in each year from the highest to the lowest (Doms and Dunne, 1998). In Figure 2 we report the mean and the median investment shares for each rank.[10] The highest investment share on average accounts for more than 20% of total investment. There is indeed a relevant degree of heterogeneity also *within* the firm: 50% of total investment is concentrated in three years only, with significantly lower investment in other years, accounting for the lumpy characteristic of the investment variable. Among possible explanations for this lumpiness is the indivisible nature of capital equipment.

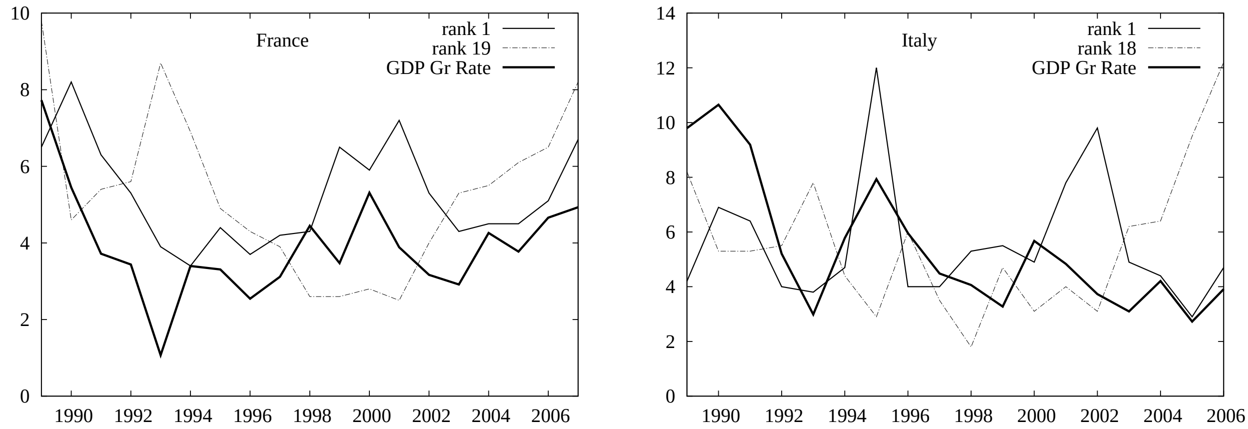
The decision of managers to pursue large investment projects is obviously related to expectations about future business opportunities. Thus, a bird's eye view of investment patterns needs to be

[10] Investment shares are, for each firm-year couple, the ratio of current (deflated) investment to the total (deflated) investment over the 19 years (18 for Italy):

$$IShare_{i,t} = \frac{I_{i,t}}{\sum_{\tau=t_0}^{t_{max}} I_{i,\tau}}$$

where $t_0 = 1989$ for both countries, and $t_{max} = 2007$ for France and $t_{max} = 2006$ for Italy. The use of this measure instead of the investment ratio allows to circumvent the lack of capital data in the French sample before 1996. Notice also that in order to compute mean and median over the same number of observations per firm, i.e. 19 years for France and 18 for Italian firms, we have to use a balanced panel. Nominal investments are deflated with the corresponding price index at the 2-digit level of industry disaggregation.

Figure 3: GDP growth rate and frequency of firm spikes in France and in Italy.



Note: *rank 1* is the highest investment episode by firm, *rank 19* is the lowest (18 for Italy).

complemented by consideration of the links between this firm micro-behaviour and the business cycle. Figure 3 plots the frequency of the highest and lowest ranks occurring in every year, and compares them with the evolution of GDP growth rates in France and Italy. Figure 3 shows that, for both countries, the rate of growth of GDP is positively correlated with the frequency of investment spikes (highest rank) and negatively correlated with the frequency of lowest values of investment (lowest rank). Firms synchronize their investment decisions in reaction to aggregate shocks: they invest more frequently during periods of expansion than during periods of contraction. This supports similar findings in Doyle and Whited (2001) and Gourio and Kashyap (2007).[11]

The descriptive analysis confirms the lumpy nature of investment at both levels of investigation. Within each firm, investments are concentrated in a few episodes, which account for a large share of each firm's total investment. At the same time, at the industry level, there is a pervasive heterogeneity in the rates of investment across firms. Most firms are involved in marginal capital adjustments which cannot be distinguished from repair and maintenance. In turn, a few firms report high rates of investment, or spikes, which are associated with large investment projects. If the interest is in studying the effects of investment on corporate performance, then it is this category of large investment episodes that should be the focus.

In order to do that, we introduce our own spike measure, the *Kernel rule*, that enables us to identify relevant episodes of investment. We then compare our measure to others proposed in the literature, namely the *Absolute rule*, the *Relative rule*, and the *Linear rule*, which have been employed in Cooper et al. (1999), Power (1998) and Nilsen et al. (2009), respectively.[12]

Figures 4 and 5 show the dependency of investment rates on firm size, for the first and second moments respectively. As shown in Nilsen et al. (2009), smaller (in terms of capital stock) firms, on average tend to display higher investment rates (Figure 4) and higher variability (Figure 5) than bigger firms. The negative relation between firm size and investment rates hints at a violation of Gibrat's law if firm size is proxied by capital.[13] A higher variability in the investment rates of smaller firms is in line with work that provides evidence of a similar relationship between firm size, in terms of sales or number of employees, and growth rates (Stanley et al., 1996).

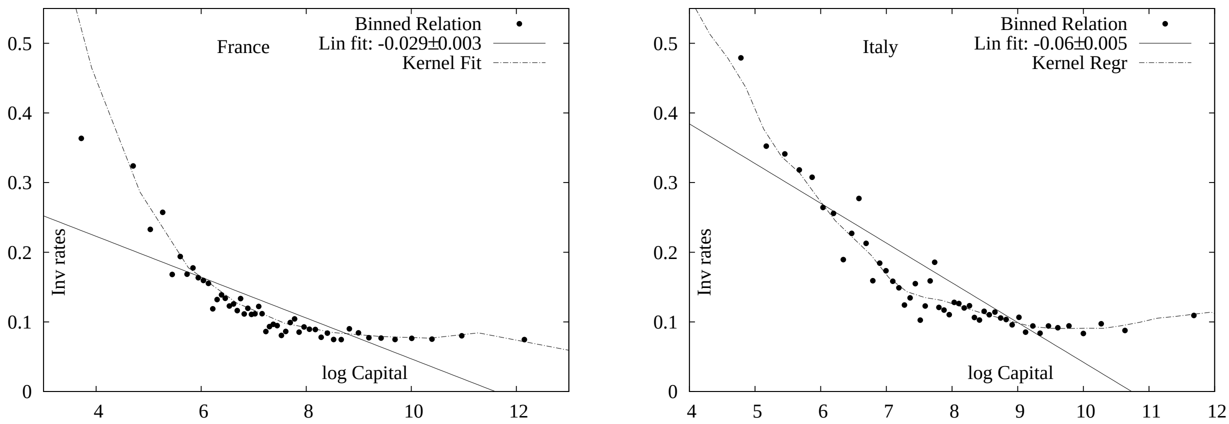
If Nilsen et al. (2009) use a linear fit to correct for the dependency of investment rates on size (see the Linear rule in the Appendix), Figure 4 shows a clear non-linear relationship between capital stock

[11]In the latter article the authors show also that the relative importance of idiosyncratic vs. aggregate shocks on firms' investment decisions depends heavily on the industry under investigation.

[12]The Appendix contains a review of the measures employed in previous empirical work on investment spikes, and it explains how we adapted those measures to data in our sample.

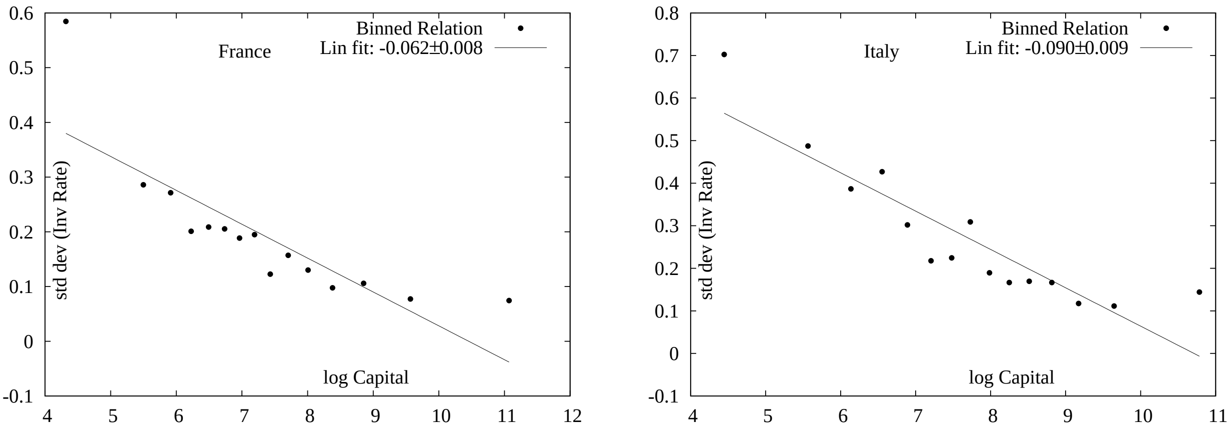
[13]Gibrat's law (refer to Gibrat, 1931 for the original contribution, and to Sutton, 1997 for a review) states that a firm's growth is independent on its size. It is also referred to as the "law of proportionate effects". Considering investment rates as capital growth rates we could therefore expect them to be independent of firm size.

Figure 4: Linear and kernel fit of the relation between size and investment rates for France (left) and Italy (right) in 2003



Note: The observations are binned into 50 groups and the mean of each bin is represented on the plot - they are shown as "Binned Relation" on the plot.

Figure 5: Log of the standard deviation of investment rates as a function of (log of) capital in 2003.



and investment rates for both the French and Italian data. In particular, the plot emphasizes that the linear fit provides an accurate description of the relationship only for firms around the median of the firm size distribution. Smaller firms have systematically higher investment rates than predicted by the linear relation, as do larger firms. In order to account for this non-linearity we employ a non-parametric kernel fit.[14] The non-parametric kernel regression is chosen to avoid imposing an ad-hoc structure on the data, and also because of the lack of a widely accepted theory to explain the relationship between capital and its growth rate.

Hence, we classify as a spike any episode where the observed investment rate is significantly higher than its expected value given the firm's size. The kernel spike dummy is identified according to the following rule:

$$S_{i,t} = \begin{cases} 1 \, \text{if} \, I_t/K_{i,t-1} > \alpha E[(I_{i,t}/K_{i,t-1})|K_{i,t-1}] \\ 0 \, \text{otherwise} \end{cases}$$

where α is set to 1.75 and the expected value is obtained through kernel estimation for each Pavitt sector-year. Note that in contrast to the rules previously used in the literature, there is no need to set

[14]Moments are computed on 20 equispaced points, Epanenchnikov kernel is used (Silverman, 1986).

Table 3: Descriptive statistics for different definitions of spikes, 1996-2007

	Absolute rule	Relative rule	Linear rule	Kernel rule	All Sample
France					
Mean investment rate	0.47	0.54	0.60	0.53	0.14
% of spikes in nb of obs.	18.28	13.18	11.58	13.45	
% of total investment accounted by spikes	28.36	20.69	27.07	34.67	
Italy					
Mean investment rate	0.53	0.58	0.59	0.53	0.12
% of spikes in nb of obs.	15.07	11.89	12.39	13.14	
% of total investment accounted by spikes	36.56	31.20	35.70	41.50	

a minimum threshold value to define the kernel spike dummy since the values of the kernel estimation never become negative.

Table 3 provides a comparison of the performance of the different spike measures. As stated by Nilsen et al. (2009), any meaningful spike measure should select episodes of investment that are larger than the unconditional investment rates. In this respect, notice that for any of the chosen definitions, the average investment rate conditional on observing a spike exceeds 0.40 which is much larger than the average over the entire sample of 0.14 for France and 0.12 for Italy. Another criterion for selection among spike rules concerns their parsimoniousness, i.e. their ability to capture a large share of total industry investment with a relatively small number of observations. According to this criterion the Kernel rule is the best measure. In France (Italy) 13.45% (13.14%) of observations are classified as spikes which account for 34.67% (41.50%) of total investment.

The evidence above suggests that spikes identified according to the Kernel rule are less likely to be biased by size dependency (see also Table A2 in the Appendix) and still they possess all the characteristics required for a spike measure, i.e. they represent a rare and large event of investment for the firm. Further, at the aggregate level, these spikes account for a large share of total investment.

4 Investment and firm performance across spike measures

In the empirical analyses that follow, we put at work our proposed spike measure. In order to enhance the comparability with findings of previous works employing other spike measures, we employ model specifications that are as close as possible to those already proposed in the literature. We study both the determinants of firm-level investment spikes and the effects of such capital adjustment episodes on firm performance. Some of the previous contributions in the literature jointly assess the relation among the firm variables before and after an investment spike (see for instance Sakellaris, 2004; Licandro et al., 2004; Nilsen et al., 2009; Asphjell et al., forthcoming). Other contributions focus disjointly on the former (Cooper et al., 1999; Bigsten et al., 1999, 2005; Letterie and Pfann, 2007; Bokpin and Onumah, 2009) or on the latter (see, among the others, Power, 1998; Bessen, 1999; Huggett and Ospina, 2001; Shima, 2010; Geylani and Stefanou, 2013). These exercises target two objectives: first, to characterize the features that increase the firm's probability to invest, which will differentiate the group of investing firms from the group of non investing firms; and second to assess the impact of the shock associated with an investment spike on firm performance, in both the short and the longer terms. Here, we run two separate analyses; first we investigate the impact of firm characteristics on the probability to observe a spike, second we focus on the effects of such spikes on firm performance after the investment episode has taken place.

Our method does not allow us to check for the causal nature of the relations under investigation. Indeed, we acknowledge the existence of endogeneity in the analysis that we carry out, as well as of possible reverse causality. The variables affecting the decision to undertake a significant investment episode are also the same variables that will be affected after the investment spike takes place. This is apparent also in the other contributions in this stream of literature. As far as this work is concerned, the interest in assessing the results of the kernel spike measures with respect to previous measures motivates the decision to perform such analysis, even in presence of such possible source of bias.

Figure 6 offers a simple visualization of the evolution of our target variables around a (kernel) spike, in the case of France and Italy. The plot in the top left of Figure 6 shows the evolution of the mean investment rate of firms before ($t-2$; $t-1$), during (t) and after (from $t+1$ to $t+4$) their investment spike. It confirms that the pattern of investment at firm level is lumpy: investment rates in the year of the event are much larger as compared to adjacent (before and after) years. The results are very similar when considering the other spike rules.

The other plots in Figure 6 show the evolution of sales growth, employment growth and productivity growth around an investment spike. In both countries, sales growth of investing firms is always positive, reaching peaks in years $t-1$ and t, before declining. Employment growth is at a maximum in year t, then declines as well. It eventually becomes negative in the case of France. The most starking difference across the two countries relates to the evolution of productivity growth around a spike. In France, investing firms report (on average) positive rates of productivity growth in all periods, but experience a severe shock at time t. Instead, in the Italian sample average productivity growth is negative in all years except in $t-1$ and $t+3$, with no clear pattern.

This first visual observation suggests important variability in performance around an investment spike. However it does not allow us to assess possible differences between the categories of investing and non-investing firms. Similarly we cannot control for firm, time or sectoral effects. The econometric analysis below addresses these issues and disentangles the determinants and effects of the relation between investment and firm performance.

4.1 Determinants of investment spikes

The theory and some early empirical works suggest that firm size, financial conditions and growth opportunities can be expected to be relevant for explaining firms' investment decisions (Nilsen and Schiantarelli, 2003; Bigsten et al., 1999, 2005; Letterie and Pfann, 2007; Bokpin and Onumah, 2009). Moreover, Sakellaris (2004) finds that employment and investment spikes are synchronized, while Asphjell et al. (forthcoming) report that employment increases before an investment spike.

4.1.1 The model

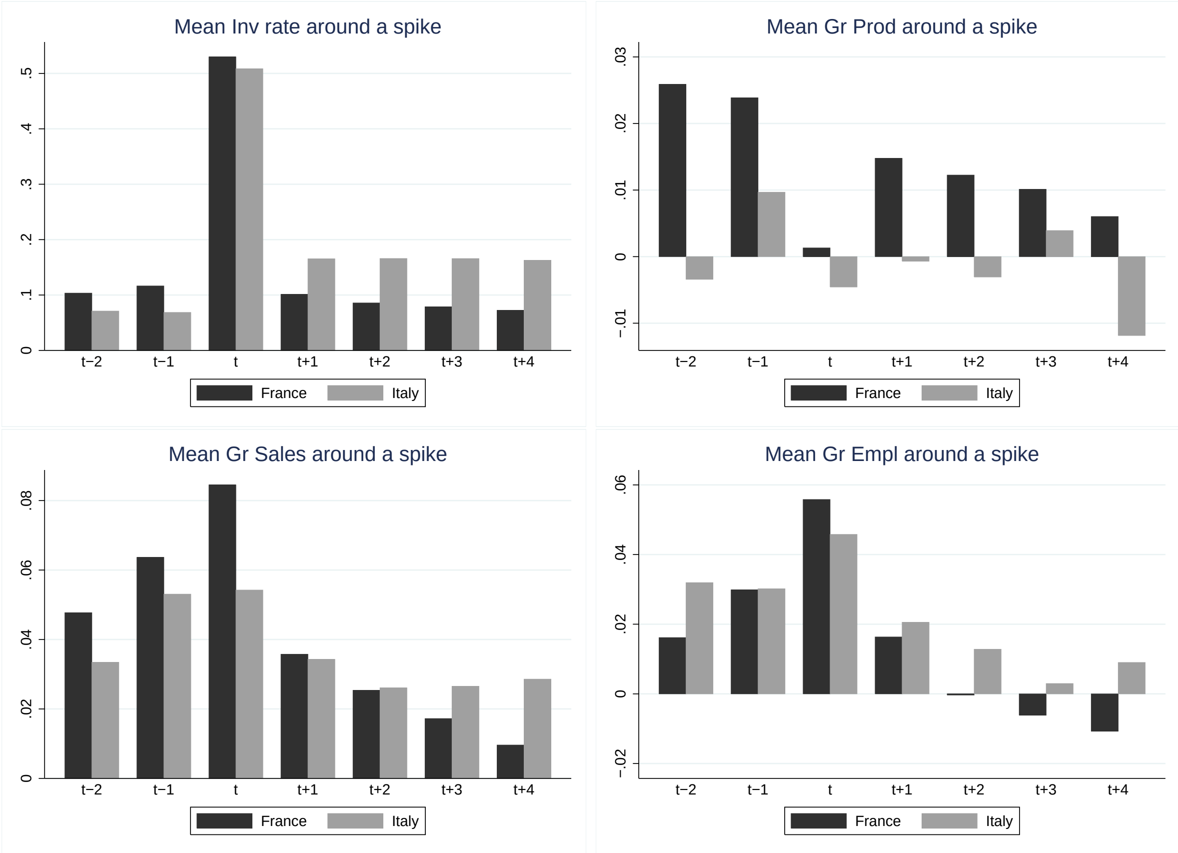
The aim of the present analysis is to enhance the understanding of the conditions that motivate and allow firms to invest. We do this by estimating the effect of firm characteristics on the probability that a firm will invest (i.e. that an investment spike is observed). We use a binary dependent variable $SPIKE_{i,t}$ that takes the value 1 if there is a spike and 0 otherwise, and we estimate the following model,

$$\text{SPIKE}_{i,t} = \beta X_{i,t-1} + \gamma D_{i,t} + v_i + u_{i,t} \tag{1}$$

where $X_{i,t-1}$ is a vector of exogenous variables observed the year before the spike, and $D_{i,t}$ is a vector of duration dummies capturing the time elapsed since the previous spike. In particular, D_1 takes the value 1 if there is a spike in year $t-1$. D_2 takes the value 1 if there is a spike in $t-2$ but not in $t-1$, and analogously D_3 takes the value 1 if there was a spike in $t-3$ but not in $t-2$ or $t-1$. Therefore these dummy variables capture the effect of a spike in a previous year, on the probability to observe a spike in year t.[15] v_i is a firm-specific unobserved random-effect and $u_{i,t}$ is a serially

[15]The duration dummies are especially meant to act as controls for recent spikes. Indeed, "multi-year spikes" (i.e., observing a spike in two or more consecutive years in the time series of a firm) are quite frequent in the data, accounting for nearly 44% and 33% respectively of the spikes in the French and Italian datasets in the case of our Kernel rule. For this reason, we go as far as three periods before the dependent variable is observed.

Figure 6: Average firm characteristics around an investment spike. France and Italy, all firms, unconditional averages.



uncorrelated logistic disturbance term. The effect of the independent variables on the probability of observing a spike is estimated using a random effects logistic regression.[16]

We run a series of specifications in which the dependent variable is alternatively defined with the Kernel rulered, the Absolute rule, the Relative rule and the Linear rule.

Independent variables include firm size, labour productivity in levels, and return on sales (RoS). As proxies for firm size we use the log of the number of employees (Empl.). In contrast to some of the specifications in the literature (Whited, 2006), we use profitability computed as RoS rather than cash flow ratio, to proxy for access to internal finance.[17] Furthermore, we consider the rates of growth of labour productivity (Prod.Growth), sales (Sales.Growth), and employment (Empl.Growth). We use a dummy to control for firms' export status at time $t-1$. Much of the recent trade literature shows indeed that the status of exporter is a prominent signal of heterogeneity among firms in the same sector (see among others Melitz, 2003; Bernard et al., 2003). Hence being an exporter could also affect the probability to observe an investment spike, and in the absence of firm fixed effects, we use the export dummy to account for such possibility.

We control also for the influence of the macroeconomic environment on firms' investment decisions, using time dummies. Figure 3 and several previous studies (Doms and Dunne, 1998; Chatelain et al., 2003; Gourio and Kashyap, 2007), show that investment decisions are determined largely by the

[16]As shown in the Appendix (Table A3), 43% of firms in France and 50% in Italy have time series without any spike. Using a fixed-effects estimator would therefore greatly reduce the sample size. Further, it would not allow to investigate the characteristics that differentiate investing and non-investing firms, and would only explain the timing of the within-firm pattern, which is our focus in the subsequent analysis (section 4.2). For the same reasons we also discard the Generalized Method of Moments.

[17]This is due to a comparability issue, indeed both the French and Italian databases provide the same set of variables to compute RoS, while the cash flow measure is computed differently for the two countries. However, in both samples, the cash flow and RoS variables are strongly correlated, indicated by a Spearman's rho coefficient of around 0.9.

Table 4: Determinants of firm-level investment for France and Italy

	France				Italy			
	Kernel rule (i)	Absolute rule (ii)	Relative rule (iii)	Linear rule (iv)	**Kernel rule** (v)	Absolute rule (vi)	Relative rule (vii)	Linear rule (viii)
Empl t-1	0.011***	-0.021***	-0.022***	0.001	0.017***	-0.016***	-0.013***	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
RoS t-1	0.187***	0.183***	0.163***	0.140***	0.150***	0.129***	0.051	0.125***
	(0.013)	(0.015)	(0.013)	(0.012)	(0.042)	(0.046)	(0.040)	(0.044)
Prod t-1	0.010***	-0.004	-0.006**	0.006***	0.024***	0.002	0.010	0.014
	(0.002)	(0.003)	(0.002)	(0.002)	(0.009)	(0.009)	(0.008)	(0.009)
Prod. Gr t-1	0.004	0.017***	0.010**	0.008**	-0.010	0.010	0.007	-0.002
	(0.004)	(0.005)	(0.004)	(0.004)	(0.012)	(0.013)	(0.011)	(0.012)
Sales Gr t-1	0.040***	0.045***	0.032***	0.034***	0.052**	0.046***	0.032**	0.049***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.016)	(0.017)	(0.015)	(0.016)
Empl. Growth t-1	0.074***	0.101***	0.070***	0.072***	-0.001	0.029	0.017	0.017
	(0.007)	(0.007)	(0.006)	(0.006)	(0.021)	(0.011)	(0.021)	(0.022)
Export t-1	0.002	-0.006**	-0.005**	-0.001	0.006	0.017	0.007	0.016
	(0.002)	(0.002)	(0.002)	(0.002)	(0.010)	(0.011)	(0.009)	(0.010)
D1	0.118***	0.169***	0.074***	0.109***	0.121***	0.135***	0.039***	0.118***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.008)	(0.009)	(0.007)	(0.008)
D2	0.058***	0.099***	0.022***	0.055***	0.072***	0.080***	0.013	0.066***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.009)	(0.008)	(0.009)
D3	0.045***	0.073***	0.022***	0.042***	0.053***	0.062***	0.009	0.048***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.010)	(0.011)	(0.010)	(0.011)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129107	131858	129997	128636	18896	19086	18445	18538
Brier score	0.1040	0.1099	0.1080	0.1051	0.1336	0.1361	0.1319	0.1339

Notes: The table reports random effects logistic regression of noted firm characteristics on the probability to observe an investment spike. D_1, D_2, D_3 are duration dummies: D_1 takes the value 1 if there is a spike in year $t-1$; D_2 takes the value 1 if there is a spike in $t-2$ but not in $t-1$; D_3 takes the value 1 if there was a spike in $t-3$ but not in $t-2$ or $t-1$. Marginal effects at means are reported, standard errors in parentheses. Asterisks denote significance levels (***: p <1%; **: p<% 5%; *: p<10%).

business cycle and the accompanying changes in demand, monetary policy, and uncertainty.

We run our set of regressions on the whole sample of observations for France and Italy, controlling for sectoral characteristics using 2-digit sectoral dummies. In the interest of space, results at the sectoral level are reported in the Appendix.

Finally, we evaluate the accuracy of the different specifications using the Brier Score (Brier, 1950) which measures the average squared deviation between the predicted probabilities of observing a spike given the estimated coefficients and the actual data.[18] Thus a lower score provides evidence of a better model performance. Results are reported in Table 4.

4.1.2 Differences across spike rules

Columns (i) and (v) of Table 4 use the Kernel rule as a dependent variable. The coefficient for the number of employees (as proxy for firm size) suggests that, in both countries, higher employment in

[18] More precisely, for each firm i, the score is given by $\frac{1}{N}\sum_{i=1}^{N}(Y_i - P_i)^2$, where N is the number of firms, Y_i is the observed event ($Y_i = 1$ if there is a spike and $Y_i = 0$ if not), and P_i is the probability that firm i experiences a spike given the estimated coefficients of the dynamic logit regression.

$t-1$ has a positive effect on the probability to observe a spike in year t. This represents a residual effect of size given that our spike measure already accounts for differences in firms' capital stock. Indeed, in the case of the spike rules which do not control for the scaling relation linking firm size (capital) to the investment rate (i.e. the Absolute and Relative rules), we report the expected negative relation between the probability to observe a spike and past employment. Because the Linear rule controls for the scaling relation in a linear way, and the regression is performed with a linear estimator, no significant residual effect of past employment on the probability to observe a spike can be observed in this last case (columns iv and viii).

The lack of a control for the scaling relation has further implications: the negative sign of the effect of labour productivity (in levels) and the export dummy should also be accounted by this bias. Indeed, the trade literature has shown that large and productive firms self-select into exporting (e.g, Bernard and Jensen, 1999; Delgado et al., 2002); in turn it is commonly found that larger firms are also more productive (see for instance Dosi et al., 2012, on the same set of data). Instead, the Linear and Kernel rules report a positive relation between past productivity and the occurrence of a spike (except for column viii, not significant), while the link with past export status is not significant. To date, the only evidence on the latter relation is of an increase in investment for firms preparing to export (López, 2009); however there is no reference to different patterns of investment for firms already in the export status.

4.1.3 Differences across countries

The results concerning the other variables are rather consistent across spike rules, however they sometimes might slightly differ between Italy and France.

Profitability has the expected sign in both countries. A higher profit rate in year $t-1$, as captured by RoS, increases the probability of a spike in the following year. In this work we do not rely on a direct measure of financial constraints; however profitability, which is our measure of the firm's capacity to self-finance, is shown to be relevant to increase the probability of carrying out an investment project. Because the probability for a (French or Italian) firm to invest is sensitive to changes in its ability to self-finance, it suggests that internal and external sources of finance are not perfectly substitutable. This can be seen as indirect evidence of the existence of financial constraints on investment. This result is consistent with previous findings (Schiantarelli, 1996; Audretsch and Elston, 2002; Whited, 2006).[19]

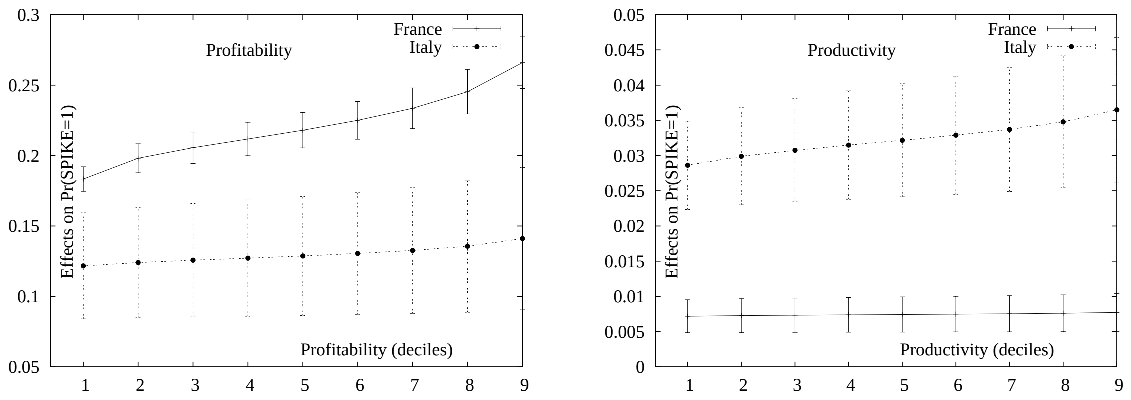
The graph on the right of Figure 7 plots for Italy and France the effects on the probability of observing a spike according to the Kernel rule, for a hypothetical firm at the independent variable means, whose productivity takes values at the distribution deciles. When the effects are computed at each decile, there is little evidence of different responses in relation to productivity. The graph on the left of Figure 7 for Italy and France, plots the effects on the probability of observing a spike (according to the kernel rule, for a hypothetical firm at the independent variable means, whose profitability varies, taking values at each distribution decile. It appears that the marginal effect of profitability on the probability of observing a spike is increasing in the value of the variable for France (solid line) but not for Italy (dashed line).

Sales growth in the previous year has a positive effect on the probability of a large investment in year t, for both France and Italy. This is coherent, for instance, with the need to expand capacity to meet growing demand. Moreover a positive effect of past sales growth also supports the conjecture that internal finance is relevant in the decision to invest at the firm level, in accordance with the previous literature (Schiantarelli, 1996; Whited, 2006).

Productivity growth however does not appear to have an influence on investment: increased productivity in the previous year is unlikely to affect an investment decision in the current year. The result for employment growth, although only significant for France, is more interesting in that it provides some insights on the timing of decisions related to hiring and investing. Increased employment

[19]Interpreting the positive relation between past profitability and investment as a sign of the presence of financial constraints is further confirmed by a test of the interaction effect between profitability and firm size, on the probability to invest. The results, not shown here, reveal that the sensitivity of investment to profitability is even greater for the category of small firms, defined as those firms whose numbers of employees are below the median.

Figure 7: Marginal effects for Profitability and Productivity (computed at distributions deciles) on the probability of having an investment spike. Error bars represent one standard error.



seems to precede an episode of capital adjustment. This finding is in line with the results in Sakellaris (2004) and Asphjell et al. (forthcoming).

The regression results also suggest that an investment spike in a previous year increases the probability of a spike in year t. This pattern, which holds for both France and Italy, suggests that large investment projects are likely to span over more than one fiscal year (in line with Cooper et al., 1999; Bigsten et al., 2005, but in contrast to Whited, 2006).[20] As a robustness check we run the same regressions without the multi-year spike observations. The results, which are not shown here, do not change significantly. Note also that, for both countries, the effect of a past spike is always positive and significant but its magnitude decreases over time: a spike three years ago explains about a third of a current spike compared to a spike in the previous year. Notice the only exception in column vii: when considering the Relative rule, and for Italian firms, the effect of past spikes is only significant at the first lag.

Finally, we conduct the analysis using Total Factor Productivity instead of labour productivity (TFP, in levels and in growth rates). Due to the lack of information about the (true) entry and exit processes in our datasets, we construct the variable following the method proposed by Levinsohn and Petrin (2003). Results, shown in Table A16 in the Appendix, are robust to the use of this alternative productivity proxy.

To sum up, our analysis of the determinants of investment spikes has revealed differences across spike rules, in particular depending on their ability to control for the scaling relation linking firm size and investment patterns. The failure to account for this fact leads to several biases in the estimation of the relation between past firm characteristics and the probability to observe a spike. Our first exercise also suggests a high degree of similarity among French and Italian firms, conferring more breadth to our findings on the determinants of investment spikes.

4.2 Effect of investment spikes on firm performance

We next explore the effects of investment spikes on firm performance. Several reasons motivate firms to invest in tangible assets; such as being able to satisfy an increasing demand, or to buffer against technological obsolescence by replacing existing machinery and equipment, or to prepare for the launch of a new series of products requiring new machinery. We would expect therefore that investment spikes should be positively correlated with firm size, firm growth, and also firm efficiency.

A number of papers investigate the link between investment and productivity, and productivity growth rates. Bessen (1999) finds that for new plants, labour productivity increases with time, which

[20] This result can be reconciled with the existence of quadratic adjustment costs or irreversible investment. In both cases, multi-year spikes can be expected, where the firm would invest in repeated years. Instead, a positive duration dependence is expected in the case of fixed adjustment costs, because the gains from investing very shortly after a first spike are very small (see the discussion in Bigsten et al., 2005, p. 5).

he attributes to a learning-by-doing process. Power (1998) also finds a positive correlation between labour productivity and plant age, and concludes that "selection and learning could be important determinants of the pattern of productivity across plants" (Power, 1998, p. 311). However, Power finds no relation with investment age. Finally, Shima (2010) reports a negative relation between technical efficiency and machinery age and Huggett and Ospina (2001) observe a fall in productivity after an investment spike.

Using a different econometric approach, Nilsen et al. (2009) find evidence of a positive and significant effect of contemporaneous (same year) investment on labour productivity, but this positive effect disappears in the following years.

The type of investment might also trigger different performance responses. If the theory expects a higher productivity effect in case the investment involves a more recent technology (Cooley et al., 1997), such information most of the time is not available in the data. Some authors have used equipment purchases as a proxy for the adoption of new technology (De Long and Summers, 1991; Huggett and Ospina, 2001). Others, as Licandro et al. (2004), have tried on the contrary to identify expansionary investment (which should have a higher impact on firm growth) or replacement investment. More precisely, the authors classify a firm as expansionary if it declares an increased number of plants in the sample period; they proxy replacement investment by an innovative firm, classified as a firm declaring more frequent process innovation. Applying this distinction, Licandro et al. (2004) find that expansionary firms show relatively strong increases in productivity levels in the year of a spike, while the impact on innovative firms' productivity is observed after a delay of four years. They explain that the former are able instantly to integrate the productivity gains from the investment, while the latter exhibit longer learning curves. Besides replicating our methodology for our four alternative spike rules as in the previous section, and across a large range of target variables, we also test whether distinct types of investment trigger different effects on firm performance. Unfortunately, due to data constraints, it is not possible to decompose the investment variable into sub-categories, hence we consider an increase in the number of plants as evidence of expansionary investment. Note however that we define expansionary episodes, while Licandro et al. (2004) identified expansionary *firms*.

4.2.1 The model

A thorough assessment of the link between productivity growth and investment spikes, requires study of the dynamics of the interrelation between the adjustment episode and other firm-level variables over time. In order to account properly for these dynamics, we rely on the methodology proposed by Sakellaris (2004) and employed, with some modifications, also by Nilsen et al. (2009).

Building on this approach, we investigate the impact of investment spikes on six performance variables including (log) sales, the (log) number of employees and (log) labour productivity. We also consider the growth rates of these variables. We regress each performance variable on a group of spike dummy variables. For each of the six regressions, taking $X_{i,t}$ as one of our variables of interest, we estimate the following model:

$$X_{i,t} = \beta D_{i,t} + \gamma_1 DBefore_{i,t} + v_i + \epsilon_{i,t} \tag{2}$$

where $D_{i,t}$ is a vector of the duration dummies composed of three elements D_{t0}, D_{t1} and D_{t2}. Similar to our investigation of the determinants of investments, D_{t0} takes the value 1 if the investment spike is contemporaneous, i.e. occurring in year t; D_{t1} takes the value 1 if the investment took place at $t-1$, but not in t and finally D_{t2} takes the value 1 if the spike occurred at $t-2$, but not in $t-1$ or in t. $DBefore_{i,t}$ is a dummy that takes the value 1 if the last investment spike was observed more than two years before t and zero otherwise. Thus the coefficient γ_1 accounts for the effect of investment spikes on long-run firm performance.

We are interested in firm-level within variation, controlling for unobserved characteristics, therefore we use a fixed-effects estimator, captured by v_i, a firm-specific unobserved fixed effect.[21] Finally, $\epsilon_{i,t}$

[21]Notice that, contrary to Section 4.1, resorting to fixed effects models when the dependent variable is not a time invariant dummy does not reduce the sample size.

is the error term. Time (year) dummies are also included, whether obviously sectoral effects are accounted for by firm level fixed effects.

We also consider a specification of the model that enables us to distinguish the effects of strictly expansionary events versus non-expansionary events. Using the number of plants, available in the French database, we construct a dummy, $DPlant_{i,t}$, which takes the value 1 if the firm has increased its number of plants between $t-1$ and t.[22] This captures expansionary episodes and allows us to study the effect of setting up a new plant on firm performance. As reported in Table A4 in the Appendix, a series of mean difference tests confirms this interpretation for the increase in the number of plants. With respect to firms not growing in terms of number of plants at time t ($DPlant_{t0} = 0$), there is a significant difference in sales and employment growth rates for at least two years in the group of firms undergoing an increase in the number of plants ($DPlant_{t0} = 1$).

Thus we estimate the following model:[23]

$$X_{i,t} = \beta D_{i,t} + \lambda DPlant_{i,t} + \gamma_1 DBefore_{i,t} + v_i + \epsilon_{i,t} \tag{3}$$

The results are presented in Tables 5 to 8. Tables 5 to 7 report the regression results for the specification presented in equation 2 and show the effect of past investment spikes on firm performance for France (columns i-iv) and Italy (columns v-viii) across the four spike rules. The second set of results (Table 8) refers to equation 3 and also considers the effect of reporting an increase in the number of plants on the performance of French firms.

In the following we present the results for the whole French and Italian samples. We also perform the analysis at the Pavitt sector level (using the Kernel rule); these additional results are in the Appendix (Tables A5-A15). Finally, as a robustness check, we perform the analysis without multi-year spike events, i.e., spikes in adjacent years, in order not to bias our analysis of the dynamic effect of investment on performance. The results, not shown here, change only in relation to a small decrease in the coefficients.

4.2.2 Differences across performance proxies

Productivity and productivity growth

Results in Table 5 (top panel) show similar patterns in France and Italy, especially in the case of the Kernel rule. There is a positive contemporaneous effect on productivity of an investment spike, D_{t0}, which persists over time: $D_{t1}, D_{t2}, DBefore$ are also positive and significant. In quantitative terms, after controlling for firm-specific fixed effects, in the year of the spike an investing firm in France is on average 0.014 log points (1.4 percent) more productive, and 0.018 log points (1.8 percent) in Italy.

In the lower panel of Table 5, where the dependent variable is productivity growth, we observe a negative shock on productivity growth in the same year for French firms, $Dt0$, representing a 0.02 log points (2 percent) decrease for the kernel rule, but this negative effect soon disappears. Instead in Italy no impact of spikes on productivity growth can be detected, whatever the spike rule under consideration.

As a robustness check we perform the same analysis also using Total Factor Productivity (TFP). The results are reported in Table A17 in the Appendix. Our findings are robust to the change in the productivity proxy, indicating that the increase in labor productivity is not due to firms' substitution of workers for capital.

Sales and sales growth

Both French and Italian firms report bigger volumes of sales following an investment spike, as shown in Table 6, top panel. The positive effect of investment spikes on sales is consistent with the hypothesis

[22] Similar to equation 2 $DPlant_{t0}$ takes the value 1 if the increase in the number of plants is contemporaneous; $DPlant_{t1}$ takes the value 1 if it occurred in $t-1$, but not in t and finally $DPlant_{t2}$ takes value 1 if the increase in the number of plants was at $t-2$, but not in $t-1$ or in t.

[23] Notice that the expenses related to the opening of a new plant does not necessary overlap with our proposed measure of investment spike. However, the investment rate in the year of the opening of a new plant tend to be rather high: the average is around 20%, as compared to an unconditional average of 14% (see Table 3).

Table 5: Effects of investment spikes on labour productivity and labour productivity growth.

	France				Italy			
	Kernel rule (i)	Absolute rule (ii)	Relative rule (iii)	Linear rule (iv)	**Kernel rule** (v)	Absolute rule (vi)	Relative rule (vii)	Linear rule (viii)
Prod.								
Dt0	0.014***	0.012***	0.008***	0.010***	0.018**	0.013*	0.011	0.016**
	(0.003)	(0.002)	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
Dt1	0.013***	0.011***	0.008***	0.011***	0.013*	0.008	0.008	0.012
	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)	(0.008)	(0.008)
Dt2	0.013***	0.009***	0.009***	0.011***	0.009	0.010	0.012	0.014
	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)	(0.008)	(0.008)
DBefore	0.018***	0.020***	0.019***	0.018***	0.016**	0.014*	0.016**	0.013*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)	(0.008)	(0.008)	(0.008)
Obs.	147451	147451	147451	147451	24726	24726	24726	24726
R-squared	0.009	0.009	0.009	0.009	0.002	0.006	0.006	0.006
Prod. Gr.								
Dt0	-0.021***	-0.018***	-0.021***	-0.023***	-0.003	-0.003	-0.005	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.009)	(0.008)	(0.009)	(0.009)
Dt1	-0.002	-0.004	-0.002	-0.002	0.002	0.000	-0.001	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.009)	(0.009)	(0.010)	(0.010)
Dt2	0.000	-0.004	0.000	-0.002	-0.006	0.007	0.009	0.011
	(0.003)	(0.003)	(0.003)	(0.003)	(0.010)	(0.010)	(0.010)	(0.010)
DBefore	-0.004*	-0.005*	-0.003	-0.004	-0.003	-0.001	0.000	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.009)	(0.009)	(0.009)	(0.009)
Obs.	147167	147167	147167	147167	24498	24498	24498	24498
R-squared	0.003	0.003	0.003	0.003	0.005	0.006	0.006	0.006

Notes. Table reports results of regression (fixed effects) for the impact of investment timing on firm performance, standard errors in parentheses. $D_{i,t}$ is a vector of the duration dummies composed of three elements D_{t0}, D_{t1} and D_{t2}. D_{t0} takes the value 1 if the investment occurs in year t; D_{t1} takes the value 1 if the investment took place at $t-1$, but not in t and finally D_{t2} takes the value 1 if the spike occurred at $t-2$, but not in $t-1$ or in t. $DBefore_{i,t}$ is a dummy that takes the value 1 if the last investment spike was observed more than two years before t and zero otherwise. Asterisks denote significance levels(*: p<0.10, **: p<0.0, ***: p<0.01) of expansion in sales following investment. The effect of investment is strongest in year t and three times as high in France with respect to Italy consistently across spike rules. Such impact decreases after the first year, but remains significantly positive two years after the event, especially in France where the coefficient $DBefore$ is as high (or even higher) as in D_{t0}.

If we consider first differences of sales, Table 6, lower panel, the contemporaneous effect of investment is also positive for both countries. Such boost in sales growth is however limited to the short term, as coefficients $Dt1$, $Dt2$, $DBefore$ are either negative (France), although of low magnitude, or not significant (Italy).

This second set of results shows that investment spikes enable the firm to increase also its capacity, as proxied by level of sales. At the same time, we do not observe a lag between the investment and the impact on revenues; in fact, the biggest effect on firm growth occurs in the same year of the investment episode.

Table 6: Effects of investment spikes on sales and sales growth.

	France				Italy			
	Kernel rule (i)	Absolute rule (ii)	Relative rule (iii)	Linear rule (iv)	**Kernel rule** (v)	Absolute rule (vi)	Relative rule (vii)	Linear rule (viii)
Sales								
Dt0	0.095***	0.068***	0.061***	0.085***	0.029***	0.025***	0.022***	0.033***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
Dt1	0.087***	0.066***	0.059***	0.082***	0.013*	0.018***	0.015**	0.025***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
Dt2	0.070***	0.054***	0.048***	0.067***	0.014	0.019***	0.017**	0.028***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
DBefore	0.091***	0.076***	0.068***	0.092***	0.023***	0.027***	0.023***	0.033***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.007)	(0.007)	(0.007)
Obs.	148086	148086	148086	148086	25008	25008	25008	25008
R-squared	0.066	0.060	0.057	0.063	0.017	0.036	0.036	0.037
Sales Gr.								
Dt0	0.028***	0.028***	0.027***	0.030***	0.024***	0.022***	0.021***	0.024***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
Dt1	-0.005**	-0.003	-0.001	-0.003	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.002)	(0.002)	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
Dt2	-0.009***	-0.007***	-0.004*	-0.007***	0.012	0.009	0.008	0.012
	(0.003)	(0.002)	(0.002)	(0.003)	(0.007)	(0.007)	(0.007)	(0.008)
DBefore	-0.016***	-0.015***	-0.013***	-0.015***	0.003	0.001	0.000	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.007)	(0.007)	(0.007)
Obs.	148085	148085	148085	148085	24918	24918	24918	24918
R-squared	0.017	0.017	0.017	0.017	0.009	0.013	0.013	0.013

Notes. Table reports results of regression (fixed effects) for the impact of investment timing on firm performance, standard errors in parentheses. $D_{i,t}$ is a vector of the duration dummies composed of three elements D_{t0}, D_{t1} and D_{t2}. D_{t0} takes the value 1 if the investment occurrs in year t; D_{t1} takes the value 1 if the investment took place at $t-1$, but not in t and finally D_{t2} takes the value 1 if the spike occurred at $t-2$, but not in $t-1$ or in t. $DBefore_{i,t}$ is a dummy that takes the value 1 if the last investment spike was observed more than two years before t and zero otherwise. Asterisks denote significance levels(*: p<0.10, **: p<0.0, ***: p<0.01)

Number of employees and growth rates

Table 5, top panel reports the results of the effects of investment spikes on employment at the firm level. The findings are broadly in line with those on sales: investment spikes are positively related with employment and the effect is persistent over time. The magnitude of the impact of an investment spike is stable and around 0.07 log points in France and 0.015 log points in Italy (somehow slightly higher when using the Linear rule in the latter case, column viii).

The results for the effect of investment spikes on employment growth (Table 5, lower panel) are also in line with the corresponding findings on sales growth. Both countries show a positive contemporaneous effect, with an impact of 0.034 log points for France and 0.023 for Italy when using the kernel rule, and similar magnitudes for the other spike definitions. After the first year, the impact decreases and becomes negative in France, and looses significance in Italy ($Dt1, Dt2, DBefore$).

Investigation of the effects of investment spikes on firms' employment decisions provides similar evidence to that on the impact on sales. We observe a net increase in employment contemporaneous to the investment spike. This result points to substantial complementarity of capital and labour inputs in the production process at the firm level, with an increase in employment both before and after the adjustment of capital (confirming similar findings by Asphjell et al., forthcoming).

4.2.3 Differences across investment types

The analysis of the effects of an increase in the number of plants per firm provides additional insights into the role played by "pure" expansionary investment.

When accounting for the occurrence of expansionary episodes proxied by the setting up of a new plant, Table 5, columns i-iv, the lasting positive effect of an investment spike on productivity in levels is confirmed. However, it is interesting that starting a new plant is not associated with higher productivity, as $DPlant_{t0}$ and $DPlant_{t1}$ are generally negative. The same dynamics is confirmed when looking at productivity growth. Overall, these results support the conjecture that purely expansionary investment episodes do not spur an increase in productivity. An additional explanation can also be brought forward, borrowing from the "learning-by-doing" argument (Jovanovic and Nyarko, 1996). When a firm opens a new plant, the new (or old) equipment has to be used by newly hired employees, who need to be trained. As in the case of the acquisition of new vintages of machines, this training reduces workers' productivity in the short-run. The theory then expects that the productivity increases in a second phase, but we do not capture it in the data.[24]

As far as sales or sales growth are concerned, the increase in the number of plants is associated to a slight short-term additional increase in total revenues (not systematic across specifications). In turn, the findings show that also expansionary events positively contribute to employment and employment growth. This positive effect is present in the same year of the investment spike for both target variables, as well as in the following ones, for employment in levels. Effects are more prevalent in the latter case than that of sales.

4.2.4 Differences across countries

Section 4.1 showed that the decision to invest in tangible assets in Italy and France is determined by similar firm characteristics; on the contrary, the analysis of the effects on firm performance following an investment spike displays significant country differences. In general we observe a stronger effect of investment episodes on French than on Italian firms. This is especially evident for the relation between investment spikes and future productivity growth. This suggests that the "missing link" between investment and productivity in Italy can be regarded among the reasons for the enduring stagnation of the economy during the period analyzed. The question of course remains as to why similar investment activities carried out in the two countries produced rather different outcomes. Besides productivity, also the magnitude of the impact of investment spikes on sales and employment is again bigger for French than for Italian firms.

[24] We thank an anonymous referee for suggesting this interpretation of the results.

Table 7: Effects of investment spikes on employment and employment growth.

	France				Italy			
	Kernel rule (i)	Absolute rule (ii)	Relative rule (iii)	Linear rule (iv)	**Kernel rule** (v)	Absolute rule (vi)	Relative rule (vii)	Linear rule (viii)
Empl.								
Dt0	0.070***	0.047***	0.043***	0.059***	0.016***	0.016***	0.013***	0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Dt1	0.071***	0.051***	0.048***	0.065***	0.019***	0.022***	0.020***	0.029***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Dt2	0.057***	0.042***	0.040***	0.053***	0.015***	0.024***	0.023***	0.029***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)	(0.005)
DBefore	0.076***	0.063***	0.057***	0.075***	0.015***	0.025***	0.024***	0.025***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)
Obs.	148060	148060	148060	148060	25879	25879	25879	25879
R-squared	0.028	0.021	0.019	0.024	0.020	0.009	0.009	0.010
Empl. Gr.								
Dt0	0.034***	0.035***	0.034***	0.035***	0.023***	0.019***	0.019***	0.020***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)
Dt1	0.004**	0.006***	0.010***	0.007***	0.008**	0.007*	0.006	0.009**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Dt2	-0.007***	-0.004**	-0.002	-0.005***	0.002	0.001	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
DBefore	-0.011***	-0.008***	-0.006***	-0.010***	-0.006	-0.006	-0.007*	-0.004
	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)
Obs.	148036	148036	148036	148036	25879	25879	25879	25879
R-squared	0.024	0.025	0.024	0.024	0.005	0.011	0.012	0.012

Notes. Table reports results of regression (fixed effects) for the impact of investment timing on firm performance, standard errors in parentheses. $D_{i,t}$ is a vector of the duration dummies composed of three elements D_{t0}, D_{t1} and D_{t2}. D_{t0} takes the value 1 if the investment occurrs in year t; D_{t1} takes the value 1 if the investment took place at $t-1$, but not in t and finally D_{t2} takes the value 1 if the spike occurred at $t-2$, but not in $t-1$ or in t. $DBefore_{i,t}$ is a dummy that takes the value 1 if the last investment spike was observed more than two years before t and zero otherwise. Asterisks denote significance levels(*: p<0.10, **: p<0.0, ***: p<0.01)

Table 8: Effects of investment spikes and new plants opening on firm performance (France only).

	Kernel rule (i)	Absolute rule (ii)	Relative rule (iii)	Linear rule (iv)	**Kernel rule** (v)	Absolute rule (vi)	Relative rule (vii)	Linear rule (viii)	**Kernel rule** (ix)	Absolute rule (x)	Relative rule (xi)	Linear rule (xii)
	Prod.				**Sales**				**Empl**			
Dt0	0.010***	0.010***	0.008***	0.008**	0.080***	0.055***	0.051***	0.070***	0.058***	0.036***	0.034***	0.048***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Dt1	0.014***	0.013***	0.011***	0.012***	0.073***	0.051***	0.048***	0.065***	0.058***	0.038***	0.038***	0.052***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Dt2	0.010***	0.009***	0.007**	0.011***	0.058***	0.040***	0.037***	0.055***	0.046***	0.029***	0.029***	0.042***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
DBefore	0.019***	0.019***	0.018***	0.019***	0.070***	0.052***	0.051***	0.070***	0.058***	0.043***	0.042***	0.056***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
DPlant t0	-0.007	-0.021***	-0.024***	-0.021**	0.011	0.007	0.011	0.008	0.012*	0.015**	0.019***	0.012*
	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)	(0.007)	(0.009)	(0.009)	(0.006)	(0.006)	(0.007)	(0.007)
DPlant t1	-0.035***	-0.041***	-0.042***	-0.043***	0.016	0.015	0.019*	0.022**	0.017**	0.022***	0.030***	0.022***
	(0.011)	(0.010)	(0.011)	(0.012)	(0.010)	(0.010)	(0.010)	(0.011)	(0.008)	(0.007)	(0.008)	(0.008)
DPlant t2	-0.016	-0.023**	-0.018	-0.026**	-0.001	-0.001	-0.006	-0.011	0.007	0.017**	0.013	0.006
	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)	(0.010)	(0.010)	(0.011)	(0.008)	(0.008)	(0.008)	(0.009)
Obs.	123040	123040.000	123040.000	123040.000	123549	123549	123549	123549	123529	123529	123529	123529
R-squared	0.009	0.009	0.009	0.009	0.047	0.040	0.039	0.044	0.026	0.018	0.018	0.022
	Prod. Gr.				**Sales Gr.**				**Empl. Gr.**			
Dt0	-0.021***	-0.016***	-0.018***	-0.021***	0.023***	0.024***	0.022***	0.024***	0.030***	0.030***	0.030***	0.030***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	-0.002	(0.002)	(0.002)	(0.002)
Dt1	0.002	-0.001	0.002	0.001	-0.004	-0.004	-0.003	-0.004	0.003	0.003	0.005***	0.006**
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	-0.002	(0.002)	(0.002)	(0.002)
Dt2	-0.002	-0.004	-0.002	-0.002	-0.009***	-0.008***	-0.005**	-0.006**	-0.007***	-0.005***	-0.002	-0.005**
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	-0.002	(0.002)	(0.002)	(0.002)
DBefore	-0.001	-0.001	0.001	-0.001	-0.011***	-0.011***	-0.010***	-0.010***	-0.007***	-0.005***	-0.004**	-0.006***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	-0.002	(0.002)	(0.002)	(0.002)
DPlant t0	-0.011	-0.033***	-0.028***	-0.032***	0.013	0.018**	0.024***	0.015*	0.017***	0.025***	0.024***	0.021***
	(0.010)	(0.009)	(0.011)	(0.011)	(0.008)	(0.007)	(0.009)	(0.009)	-0.006	(0.005)	(0.006)	(0.006)
DPlant t1	-0.015	-0.005	-0.005	-0.014	-0.014	-0.004	0.007	-0.011	-0.001	0.002	0.011	0.005
	(0.013)	(0.012)	(0.012)	(0.013)	(0.010)	(0.010)	(0.010)	(0.011)	-0.007	(0.007)	(0.007)	(0.008)
DPlant t2	0.007	0.009	0.012	-0.002	-0.014	-0.014	-0.015	-0.023**	0.005	0.004	0.004	0.006
	(0.014)	(0.013)	(0.013)	(0.014)	(0.011)	(0.010)	(0.010)	(0.011)	-0.008	(0.007)	(0.007)	(0.008)
Obs.	122822	122822	122822	122822	123548	123548	123548	123548	123510	123510	123510	123510
R-squared	0.002	0.002	0.002	0.003	0.011	0.012	0.011	0.011	0.022	0.023	0.021	0.021

Notes. Table reports results of regression (fixed effects) for the impact of investment timing on firm performance, standard errors in parentheses. $D_{i,t}$ is a vector of the duration dummies composed of three elements D_{t0}, D_{t1} and D_{t2}. D_{t0} takes the value 1 if the investment occurs in year t; D_{t1} takes the value 1 if the investment took place at $t-1$, but not in t and finally D_{t2} takes the value 1 if the spike occurred at $t-2$, but not in $t-1$ or in t. $DBefore_{i,t}$ is a dummy that takes the value 1 if the last investment spike was observed more than two years before t and zero otherwise. $DPlant_{t0}$ takes the value 1 if the increase in the number of plants is contemporaneous; $DPlant_{t1}$ takes the value 1 if it occurred in $t-1$, but not in t and finally $DPlant_{t2}$ takes value 1 if the increase in the number of plants was at $t-2$, but not in $t-1$ or in t. Asterisks denote significance levels(*: p<0.10, **: p<0.0, ***: p<0.01)

Finally, if our results from section 4.1 presented important discrepancies across spike rules, the above findings do not depend on the way the investment spikes are identified.

5 Conclusions

The present paper examined the pattern of firm-level investments in France and Italy. We investigated the characteristics that make it more likely that a business company will invest, and the effects on firm performance following an investment spike. Using data on the acquisition of tangible assets we provide the first large-scale study for France and Italy documenting the lumpy nature of investments, confirming previous findings for other countries (see, among the others Doms and Dunne, 1998; Nilsen et al., 2009).

We propose a new methodology for identifying investment spikes that allows the researcher to disentangle repair and maintenance episodes from large adjustments in the stock of tangible assets. We call our proposed measure 'Kernel rule', because of how it is constructed. It allows for better correction of size dependence than other existing methods, and it also retains all the desired properties of a spike measure.

In the empirical analyses that follow we evaluate the potential differences that might emerge across four dimensions: i) different definitions of spike rules; ii) countries, Italy and France; iii) performance proxies; and iv) investment types. The analysis of the determinants of investment spikes emphasizes many similarities between France and Italy. Fast growing, profitable and productive firms are more likely to invest, both in France and in Italy. The probability of observing an investment spike is higher if there have been past investment episodes, but this positive effect decreases over time. Further, we found that export status is not systematically associated with a higher probability to invest. We observe relevant differences across spike rules, in particular depending on their ability (or inability) to control for the non-linear scaling relation linking firm size and investment patterns. The failure to account for this fact leads to several biases in the estimation of the relation between past firm characteristics and the probability to observe a spike.

We also investigate how our proposed spike measure enables to capture the effects following an investment episode. After controlling for firm characteristics, we find that investment spikes are associated with higher productivity, sales and employment. The availability, for France only, of the number of plants per firm allowed us to investigate the pattern of firm performance after the opening of a new plant. This event, which captures expansionary investment episodes, has a negative effect on productivity, but is associated with higher employment and it also positively affects firm growth rates. Taken together, our findings point to positive effects of investment on firm performance and shed some new light on the relations between technical change and employment which are worth of further investigation.

Finally, most of the differences between France and Italy emerged from the investigation of firm performance following an investment spike. The impact of investment on Italian firms is more nuanced for most indicators. We find that on average, investment spikes have a weaker impact on firm growth, and no impact on productivity growth. The relatively lower ability of Italian firms to convert investments in tangible assets into higher levels of performance contributes to explain the poor performance of Italian manufacturing firms in recent years (OECD, 2012).

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Appendix to Dynamics of Investment and Firm Performance: Comparative evidence from manufacturing industries

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This Appendix contains additional information on the data and reports results that complement the findings of the paper "Dynamics of Investment and Firm Performance: Comparative evidence from manufacturing industries".

Appendix 1. French and Italian firm-level data

The paper employs data from two similar firm-level databases for France and Italy, respectively, the Enquête Annuelle d'Entreprise (EAE) and Micro.3.[1] The two databases are much similar in that they both contain variables from firm's balance sheet and they have a common cut-off point of 20 employees. However, in both cases, the data collection process has been adapted over the years. The criteria for inclusion and the definition of the variables have changed over time. Changes to the definition of the variables in particular reflect the required adoption of European Union directives and regulations.[2] Some variables, such as capital stock, are not available for the whole French sample before 1996,[3] while in the Italian database, after 1997 the census of firms includes only companies with more than 100 employees. For employment in the range 20-99, ISTAT monitors a "rotating sample" which varies every five years. In order to increase the coverage of firms in the range 20-99, in 1998 Micro.3 started to collect data from the financial statements that limited liability firms, under Italian law, are required to disclose.[4] However, standard data from company accounts do not include observed investment, which means that the higher number of observations available from this other source is of no benefit for our study. In the interest of achieving a more homogeneous cross-country database we dropped the first years from Micro.3 and EAE and focus on the period 1996-2006 (2007 for France).[5] Also, given our interest in tracking the performance of firms over time, we consider only firms reporting data for more than three years. More details on Italian firm-level data are in Grazzi et al. (2009).

Table A1 of this Appendix groups together all the variables used in the empirical analysis and their definitions.

[1]Both databanks were made available to the authors under the mandatory condition of censorship of individual information. The Micro.3 database was developed in a collaboration between the Italian Statistical Office (ISTAT) and members of the Laboratory of Economics and Management of Scuola Superiore Sant'Anna, Pisa. More detailed information on the development of the Micro.3 database can be found in Grazzi et al. (2009).

[2]Since 1978, the process of harmonization of accounting standards has resulted in changes to national legislation: 78/660/EEC on the annual accounts of certain types of companies, 83/349/EEC on consolidated accounts, 86/635/EEC on the annual accounts and consolidated accounts of banks and other financial institutions and 91/674/EEC. Directive 2006/46/EC of the European Parliament amended the above sources.

[3]This is because before 1996, firms between 20 and 99 employees were surveyed with a simplified questionnaire.

[4]Limited liability companies (*società di capitali*) have to provide a copy of their financial statements to the Register of Firms at the local Chamber of Commerce.

[5]Notice that, for descriptive purposes, Figure 2 and 3 of the paper employ the whole span of the available sample period, 1989-2007 (2006 for Italy).

Appendix 2. Firm-level measures of Investment spikes

We present here a short description of the different measures of investment spikes already existing in the literature and we explain how we adapted them to our sample of data. This appendix also provides additional evidence on the relative performance of the *Kernel rule* vis à vis other proposed spike measures.

Power (1998) (p. 303) underlined the difficulties associated with identifying an appropriate measure to capture investment spikes: "Since an 'investment spike' is a theoretical rather than a numeric or algebraic concept, and lacks an unambiguous real-world analogue, there is some risk of measurement error, whichever definition of investment spike is employed.". However, there are some criteria that can be used to identify a spike measure. Nilsen et al. (2009) state that the investment must be large in relation to the firm's history and to the cross section of the industry, and must be a rare event. Also, the definition of a spike must be able to account for a relevant share of total industry investment. Nilsen et al. (2009) hint, too, at the necessity to account for a possible relationship between investment rate and capital stock.

We discuss four alternative methodologies to identify investment spikes, namely the *Absolute rule*, the *Relative rule*, the *Linear rule* and finally the *Kernel rule*. The first three are from Cooper et al. (1999), Power (1998) and Nilsen et al. (2009), respectively. The last is our contribution to identifying investment spikes, and overcomes some of the shortcomings of the other three measures.

The first investment spike proxy we consider classifies lumps as investment rates above a threshold that is fixed across firms and industries, hence our label the Absolute rule. To increase comparability of results with previous studies we pick 0.20 as the threshold value, following Cooper et al. (1999) and other work. The purpose of this threshold is to eliminate routine maintenance expenditure.

Some, such as Power (1998) consider spikes as large investment events relative to each firm's investment behavior. According to this rule, all investment events that are larger than a multiple α of the firm's median investment rate over the period of interest, τ, are spikes:

$$I_{i,t}/K_{i,t-1} > \alpha \operatorname*{median}_{\tau}(I_{i,\tau}/K_{i,\tau-1})$$

Power (1998) considers different values of α and finally chooses the value of 1.75;[6] we also choose this value for α. This methodology presents the problem that half of the observations classified as spikes according to the relative rule, correspond to investment rates below 0.20: for firms with very low median investment rates, spikes would not correspond to very active investment behavior in absolute terms. We impose a threshold on the minimum value of the investment rate, resulting in the spike dummy $S_{i,t}$ being identified according to the following rule:[7]

$$S_{i,t} = \begin{cases} 1 \,\text{if}\, I_t/K_{i,t-1} > \max[\alpha \operatorname*{median}_{\tau}(I_{i,\tau}/K_{i,\tau-1}), 0.20] \\ 0 \,\text{otherwise} \end{cases}$$

In what follows we refer to this spike measure as the Relative rule.

As already acknowledged by Nilsen et al. (2009), there is a problem with traditional spike measures concerning the relation between firm size and investment rate. In order to correct for the excessive volatility of investment by smaller firms, Nilsen et al. (2009) propose that, instead of imposing a homogeneous threshold for all firms, the threshold value is conditioned on the size of the firm. In particular, Nilsen et al. (2009) show the existence of a negative relation between the firm's capital stock and its investment rate, and characterize this relation within a linear model.[8] The estimated value can be negative, hence Nilsen et al. (2009) define a spike as a maximum between the expected value and a minimum threshold of 0.20. In the case of the Italian and French data in Figure 4 of the

[6]Power (1998) reports that the results do not change much with the threshold, therefore the author picks the value at which the number of investment episodes that will be discarded is the lowest.

[7]This rule which combines the thresholds in Power (1998) and Cooper et al. (1999) is also used by Licandro et al. (2004).

[8]They estimate the following linear relation between observed investment rates and the log of capital: $I_{i,t}/K_{i,t-1} = \gamma_0 + \gamma_1 \ln K_{i,t-1} + e_{i,t}$. Then they use the estimated value of the investment rate $E[(I_{i,t}/K_{i,t-1}|K_{i,t-1}]$ to identify the spikes.

paper, occurrences of negative values arise because the linear fit constantly underestimates investment rates for large values of capital. Accordingly, spikes are identified by the following rule:

$$S_{i,t} = \begin{cases} 1 \,\text{if}\, I_t/K_{i,t-1} > \max[\alpha E[(I_{i,t}/K_{i,t-1})|K_{i,t-1}], 0.20] \\ 0 \,\text{otherwise} \end{cases}$$

where α also takes value 1.75. In what follows we refer to this spike measure as the Linear rule.

Table 3 in the paper shows that the Kernel rule is able to account for the size dependency and at the same time it still possesses all the characteristics required for a spike measure. Table A2 of this Appendix provides a comparison of how the various measures proposed in the literature are able to adjust for such size dependency. The table compares the unconditional distribution of the entire sample with the distributions of observations classified as spikes according to the four definitions provided above.

the distribution of the whole dataset over three size classes to the conditional ones, where only the observations identified as spikes according to the four definitions are kept. It is apparent that both the Absolute and Relative rules suffer from a size bias: observations classified as spikes according to these rules over-represent small firms compared to the whole population, whereas larger firms are underrepresented. The Linear rule offers a slight improvement in relation to this bias, but the kernel measure has the biggest effect on reducing the size bias.

Appendix 3. Analysis at the sectoral level

The econometric analysis presented in the paper is performed pooling observations from all manufacturing industries and controlling for sectoral differences by means of dummies.

This is an effective way to report results for numerous sectors, condensed within a few tables. However this choice also includes the inconvenience of imposing a common structure on the data because it does not allow the coefficients we are most interested in, to vary across sectors. In an attempt to reconcile for sectoral variability and to keep the number of tables as small as possible, we group firms according to the Pavitt taxonomy (Pavitt, 1984) which accounts for different sources of technology, user requirements, and intellectual property regimes. 3-digit NACE sectors are matched with the four Pavitt sectors, following the correspondence table in Dosi et al. (2008). In the "supplier-dominated" sector, technology is acquired through the purchase of new intermediate inputs and includes among others the textile, clothing and metal products sectors. The "scale-intensive" sector is characterized by industries for which economies of scale make it important to acquire a large production capacity, such as for chemicals, agricultural products and motor vehicles. The "specialized supplier" sector includes machine-tools and electrical equipment; and the "science-based" sector includes those industries where science and research and development are important, e.g. pharmaceuticals, electronics and computer producers. Since Pavitt's taxonomy is a typology based on sectoral innovation processes it would seem appropriate also for categorizing firms according to their investment patterns: investment opportunities, scale of production, technology and capital intensity, need to buy in technology versus producing it internally, are all features strongly related to the firm level investment decision.

Therefore in this Appendix we run the same specifications of the paper on the four macro industrial sectors according to Pavitt's taxonomy. The results reported below consider the Kernel rule for identifying investment spikes.

3.1. Determinants of Investment spikes by Pavitt sector

Tables A5 and A6 in this Appendix report the results of the specifications presented in Table 4 of the paper for the four macro industrial sectors, identified by Pavitt's taxonomy. The results of the sectoral level analyses are in line with those for the entire sample. Table A5 shows that size, return on sales, productivity and past spikes have a positive and significant effect on the probability of an investment spike, which is in line with the results for the entire sample (Table 4 columns i, ii and v). Nevertheless there is some heterogeneity in the strength of these impacts across sectors. For example RoS has a weaker impact in the French science-based sector and is not significant in the Italian supplier-dominated and science-based sectors. This points to differences in reliance on self-financing across sectors. Table A6 mostly confirms the results, at the aggregate level, when variables in first differences are included. Although productivity growth has no significant impact for the whole sample of French firms, we find a negative relation for the science-based sector (Table A6). Also, in this sector for France, the probability of investment is strongly associated with a past increase in sales (with a coefficient much higher than for other sectors), but not with an increase in the employee numbers. Finally, although the export dummy turns out not to be significant for explaining an investment spike, the sectoral analysis shows some differences for the French dataset: the export dummy is significant and positive for the scale-intensive sector and significant and negative for the supplier-dominated sector.

3.2. Investment spikes and firm performance by Pavitt sector

The results in Tables 5 and 6 of the paper consider the whole sample of firms for France and Italy and control for differences across industries using sectoral dummies. In this Appendix Tables A7 to A15 report results of the regressions for the four sectoral subsamples.

In relation to labour productivity, Table A7 shows a positive effect of investment spikes for France and Italy confirming results at the aggregate level, Table 5, columns (i) and (vii) of the paper. However, we observe diverging patterns across sectors and countries. Both in France and Italy, the positive effect is rather long term in the scale intensive sector (with a highest coefficient more than two years after the spike, $DBefore$), and instead rather short term in the specialized supplier sector. Moreover, in the science-based sector the impact is positive but quite heterogeneous across firms, therefore only significant two years after the spike, $Dt2$. In the supplier dominated sector (containing for ex. the textile industry), investment spikes are associated with a higher productivity in the French sample at all lags considered whereas no effect can be detected in the Italian case. Finally, the opening of a new plant incurs a negative productivity shock in the supplier dominated and specialized supplier groups as in the overall sample (Table A13).

Table A8 validates the findings at aggregate level for the link between investment spikes and productivity growth. We observe a short-term negative shock in all sectors but the science based in the case of France, as well as in the Italian supplier dominated group. Results reported in Table A13 are consistent with sectoral effects on productivity levels: expansionary investment spikes are associated with a negative shock on productivity growth in the supplier dominated group, besides we find a contemporaneous positive effect of an increase in the number of plants in the scale intensive sector.

One might have expected a stronger impact of investment on productivity for the science-based sector due to the higher returns on investment, and a weaker impact for the scale-intensive sector where investment might be driven by capacity expansion. Instead, we find that the productivity of science-based firms is hardly affected by investment, while expansionary investment in the scale-intensive sector enhances productivity. One possible interpretation of this result is that gains in productivity for firms in the science-based sector are related more to intangible assets or a skilled workforce than to investment in tangible assets. The reverse is true for the scale-intensive sector, where increasing the number of operating plants and investing allows further gains in productivity due to scale economies.

Finally, Tables A9 to A12 in this Appendix almost mirror Table 5 and 6 in the paper for the link between investment spikes and sales, sales growth, employment, and employment growth. Investment allows for increases in size measured as sales and number of employees, in all sectors, although the benefits are more important for French firms. Note that the size effects are systematically highest in the science based sector and lowest in the supplier dominated sector. Moreover, diverging sectoral patterns are apparent in Tables A14 and A15: the growth effects of expansionary investments are positive in the scale intensive sector and negative in the specialized supplier and science based sectors, mirroring the efficiency gains and losses.

Summing up the evidence at the sectoral level, for most of the cases analyzed above the results at the aggregate level still hold for the separate Pavitt sectors. However there are some differences. In particular, firms in the scale-intensive sector appear to gain most from setting up a new plant and this result supports the conjecture that for this sector, scale-economies are more relevant than for the other ones.

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Table A1: Variables definition

Inv. rate	Investment rate	I_t/K_{t-1}
Empl	Number of employees (log)	$log(Empl_t)$
Empl. growth	Growth of employment	$log(Empl_t) - log(Empl_{t-1})$
Prod	labour Productivity (log)	$log(Prod_t) = log(VA_t/Empl_t)$
Prod. growth	Growth of labour productivity	$log(Prod_t) - log(Prod_{t-1})$
Sales	Total Sales (log)	$log(Sales_t)$
Sales growth	Growth of total sales	$log(Sales_t) - log(Sales_{t-1})$
RoS	Return on sales	$RoS_t = GOM_t/Sales_t$
Plant	Number of plants	
Export	Export dummy	= 1 if Exports> 0
D1	Spike dummy	= 1 if spike at t-1
D2	Spike dummy	= 1 if spike at t-2, but not in t-1
D3	Spike dummy	= 1 if spike at t-3, but not in t-1 or t-2
Dt0	Spike dummy	= 1 if spike at t
Dt1	Spike dummy	= 1 if spike at t-1, but not in t
Dt2	Spike dummy	= 1 if spike at t-2, but not in t-1 or t
DBefore	Spike dummy	= 1 if spike occurred before t-2
DPlant t0	Expansionary inv. dummy	= 1 if increase in nb of plants in t
DPlant t1	Expansionary inv. dummy	= 1 if increase in nb of plants in t-1 but not in t
DPlant t2	Expansionary inv. dummy	= 1 if increase in nb of plants in t-2 but not in t or t-1

Table A2: Share of observations per size class across different spike measures, 1996-2007.

Size class	All sample	Absolute rule	Relative rule	Linear rule	Kernel rule
France					
Small	17.51	32.33	31.52	25.15	18.35
Medium	67.78	60.81	61.85	64.11	67.64
Large	14.71	6.86	6.63	10.73	14.01
Italy					
Small	8.56	13.5	13.77	11.05	6.20
Medium	65.53	69.2	68.90	68.24	65.00
Large	25.09	17.2	17.33	20.71	28.00

Note: "Small" $lnK < 6$, "Medium" $6 \leq lnK < 9$ and "Large" $lnK \geq 9$.

Table A3: Distribution of number of spikes per firm (Kernel rule)

Nb spikes	France (share)	Italy (share)
0	42.43	50.17
1	26.33	27.53
2	15.78	13.10
3	7.87	5.51
4	4.14	2.21
5	1.92	0.86
More than 5	1.52	0.62
Total	100.00	100.00

Table A4: Mean difference tests (France only)

	(1) $DPlant_{t0} = 0$ mean	(1) $DPlant_{t0} = 0$ sd	(2) $DPlant_{t0} = 1$ mean	(2) $DPlant_{t0} = 1$ sd	t-test	W-M-W test
Empl. Gr. (t)	0.003	0.000	0.027	0.002	(1) < (2)***	(1) < (2)***
Empl. Gr. (t+1)	0.001	0.000	0.007	0.003	(1) < (2)***	(1) < (2)***
Empl. Gr. (t+2)	-0.002	0.001	-0.001	0.003	(1) = (2)	(1) = (2)
Sales Gr. (t)	0.026	0.001	0.047	0.003	(1) < (2)***	(1) < (2)***
Sales Gr. (t+1)	0.024	0.001	0.036	0.004	(1) < (2)***	(1) < (2)***
Sales Gr. (t+2)	0.018	0.001	0.032	0.004	(1) < (2)***	(1) < (2)***

Note: $DPlant_{t0} = 1$ refers to the "Expansion" sample, including firms with a positive growth in their number of plants at time t. We report the significance of the t-test of the difference in means and the Wilcoxon-Mann-Whitney equality tests as follows: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table A5: Determinants of Investment by Pavitt sector (column i, ii and v from Table 4 of the paper).

	France								**Italy**			
	Supplier Dominated		Scale Intensive		Specialized Suppliers		Science Based		Supplier Domin	Scale Inten	Specialized Suppl	Science Based
Empl t-1	0.016***		0.016***		0.013***		0.008**		0.024***	0.018***	0.012	0.012
	(0.001)		(0.002)		(0.002)		(0.003)		(0.005)	(0.004)	(0.008)	(0.009)
Plant t-1		0.012***		0.010**		0.012***		-0.002				
		(0.002)		(0.004)		(0.004)		(0.007)				
RoS t-1	0.219***	0.234***	0.266***	0.266***	0.266***	0.266***	0.069***	0.061*	0.045	0.138**	0.322***	0.176
	(0.017)	(0.017)	(0.027)	(0.027)	(0.034)	(0.034)	(0.040)	(0.037)	(0.066)	(0.063)	(0.100)	(0.139)
Prod t-1	0.023***	0.017***	-0.010	-0.009	0.003	0.004	0.008	0.010	0.065***	0.022***	0.011	-0.045
	(0.003)	(0.003)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)	(0.012)	(0.011)	(0.023)	(0.028)
Export t-1	-0.007***	-0.001	0.015***	0.023***	0.000	0.006	0.009	0.014	0.002	- 0.013	-0.022	0.076
	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.006)	(0.010)	(0.009)	(0.014)	(0.014)	(0.028)	(0.055)
D1	0.124***	0.124***	0.130***	0.128***	0.137***	0.136***	0.161***	0.160***	0.126***	0.112***	0.169***	0.166***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.008)	(0.008)	(0.012)	(0.012)	(0.012)	(0.012)	(0.019)	(0.024)
D2	0.058***	0.058***	0.063***	0.061***	0.067***	0.066***	0.075***	0.075***	0.072***	0.065***	0.119***	0.085***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.008)	(0.008)	(0.012)	(0.012)	(0.013)	(0.013)	(0.020)	(0.033)
D3	0.045***	0.045***	0.046***	0.045***	0.059***	0.058***	0.050***	0.048***	0.072***	0.035**	0.092***	0.039
	(0.004)	(0.004)	(0.007)	(0.007)	(0.008)	(0.008)	(0.014)	(0.014)	(0.016)	(0.016)	(0.026)	(0.045)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76221	76187	30565	30562	19776	19776	7232	7220	7545	7806	3430	1028
Brier score	0.1103	0.1107	0.1054	0.1062	0.1068	0.1071	0.1025	0.1027	0.1356	0.1369	0.1413	0.1203

Notes: Table reports random effects logistic regression of noted firm characteristics on the probability to observe an investment spike. Marginal effects are reported, standard errors in parentheses. Asterisks denote significance levels (***: p <1%; **: p<% 5%; *: p<10%).

Table A6: Determinants of Investment by Pavitt sector (columns iii, iv and vi from Table 4 of the paper).

	France								Italy			
	Supplier Dominated		Scale Intensive		Specialized Suppliers		Science Based		Supplier Domin	Scale Inten	Specialized Suppl	Science Based
Empl t-1	0.013***		0.013***		0.010***		0.007**		0.023***	0.016***	0.011	0.008
	(0.001)		(0.002)		(0.002)		(0.003)		(0.005)	(0.004)	(0.008)	(0.010)
Plant t-1		0.010***		0.009**		0.008*		-0.001				
		(0.002)		(0.004)		(0.004)		(0.006)				
RoS t-1	0.176***	0.187***	0.230***	0.230***	0.212***	0.210***	0.075*	0.068*	0.056	0.163**	0.343***	0.226
	(0.018)	(0.018)	(0.027)	(0.027)	(0.035)	(0.035)	(0.039)	(0.039)	(0.070)	(0.065)	(0.102)	(0.145)
Prod t-1	0.025***	0.021***	-0.004	-0.003	0.010	0.012	0.006	0.008	0.067***	0.021*	- 0.003	-0.061*
	(0.003)	(0.003)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)	(0.013)	(0.011)	(0.024)	(0.032)
Prod. Growth t-1	0.006	0.006	0.003	-0.002	0.007	0.006	-0.029**	-0.029**	- 0.009	-0.013	-0.014	-0.008
	(0.006)	(0.006)	(0.008)	(0.008)	(0.013)	(0.012)	(0.013)	(0.013)	(0.021)	(0.017)	(0.031)	(0.046)
Sales. Growth t-1	0.045***	0.045***	0.027***	0.026***	0.012	0.013	0.114***	0.112***	0.030	0.052**	0.088***	0.070
	(0.007)	(0.007)	(0.009)	(0.010)	(0.013)	(0.012)	(0.018)	(0.018)	(0.028)	(0.025)	(0.032)	(0.070)
Empl. Growth t-1	0.071***	0.075***	0.077***	0.080***	0.114***	0.116***	0.032	0.037	- 0.024	0.009	-0.024	0.082
	(0.009)	(0.009)	(0.014)	(0.013)	(0.019)	(0.019)	(0.025)	(0.025)	(0.037)	(0.031)	(0.055)	(0.089)
Export t-1	-0.005**	-0.001	0.014***	0.020***	0.000	0.004	0.008	0.012	0.004	- 0.001	-0.022	0.097
	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.006)	(0.009)	(0.009)	(0.015)	(0.015)	(0.030)	(0.057)
D1	0.114***	0.113***	0.124***	0.122***	0.128***	0.128***	0.144***	0.144***	0.123***	0.105***	0.165***	0.148***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.008)	(0.008)	(0.013)	(0.013)	(0.012)	(0.012)	(0.019)	(0.024)
D2	0.056***	0.056***	0.063***	0.062***	0.066***	0.066***	0.072***	0.072***	0.069***	0.063***	0.113***	0.081**
	(0.004)	(0.004)	(0.006)	(0.006)	(0.007)	(0.007)	(0.012)	(0.012)	(0.013)	(0.013)	(0.020)	(0.032)
D3	0.043***	0.044***	0.046***	0.045***	0.059***	0.058***	0.047***	0.045***	0.071***	0.032	0.089***	0.036
	(0.004)	(0.004)	(0.007)	(0.007)	(0.008)	(0.008)	(0.013)	(0.013)	(0.016)	(0.016)	(0.025)	(0.043)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73536	73510	29551	29548	19076	19076	6944	6932	7168	7458	3280	990
Brier score	0.1062	0.1064	0.1012	0.1017	0.1023	0.1025	0.0957	0.0958	0.1329	0.1343	0.1379	0.1167

Notes: Table reports random effects logistic regression of noted firm characteristics on the probability to observe an investment spike. Marginal effects are reported, standard errors in parentheses. Asterisks denote significance levels (***: p <1%; **: p<% 5%; *: p<10%).

Table A7: Effect of spikes on productivity by Pavitt sector, firm-level fixed effects.

	France				Italy			
	Supplier Domin	Scale Inten	Specialized Suppl	Science Based	Supplier Domin	Scale Inten	Specialized Suppl	Science Based
Dt0	0.013***	0.011*	0.018***	0.011	-0.009	0.031***	0.041***	0.054
	(0.003)	(0.006)	(0.007)	(0.014)	(0.011)	(0.012)	(0.014)	(0.038)
Dt1	0.011***	0.011*	0.014*	0.020	-0.014	0.028***	0.037***	0.015
	(0.004)	(0.006)	(0.007)	(0.015)	(0.011)	(0.014)	(0.016)	(0.039)
Dt2	0.010***	0.008	0.017**	0.036**	-0.011	0.021	0.005	0.066***
	(0.004)	(0.006)	(0.007)	(0.015)	(0.012)	(0.014)	(0.016)	(0.039)
Dbefore	0.018***	0.028***	0.004	0.018	-0.003	0.037***	-0.001	0.041
	(0.003)	(0.005)	(0.006)	(0.013)	(0.010)	(0.013)	(0.014)	(0.035)
R-squared	0.004	0.009	0.053	0.073	0.010	0.010	0.027	0.023
Obs.	83788	33716	21871	8076	9458	9667	4296	1305

Table A8: Effect of spikes on productivity growth by Pavitt sector, firm-level fixed effects.

	France				Italy			
	Supplier Domin	Scale Inten	Specialized Suppl	Science Based	Supplier Domin	Scale Inten	Specialized Suppl	Science Based
Dt0	-0.024***	-0.016**	-0.016**	-0.026	-0.025*	0.016	-0.005	-0.001
	(0.004)	(0.007)	(0.008)	(0.016)	(0.013)	(0.014)	(0.021)	(0.041)
Dt1	-0.004	0.001	0.002	-0.004	0.000	0.003	0.001	-0.005
	(0.004)	(0.007)	(0.008)	(0.017)	(0.014)	(0.016)	(0.023)	(0.043)
Dt2	-0.005	0.007	0.003	0.011	0.002	-0.009	-0.031	0.032
	(0.004)	(0.007)	(0.008)	(0.017)	(0.014)	(0.017)	(0.023)	(0.043)
DBefore	-0.004	-0.002	-0.009	-0.015	-0.008	0.005	-0.011	0.003
	(0.003)	(0.006)	(0.007)	(0.014)	(0.012)	(0.015)	(0.021)	(0.038)
R-squared	0.003	0.003	0.003	0.006	0.006	0.011	0.016	0.009
Obs.	83654	33634	21832	8047	9383	9563	4259	1293

Table A9: Effect of spikes on sales by Pavitt sector, firm-level fixed effects.

	France				Italy			
	Supplier Domin	Scale Inten	Specialized Suppl	Science Based	Supplier Domin	Scale Inten	Specialized Suppl	Science Based
Dt0	0.086***	0.103***	0.095***	0.150***	0.023**	0.023**	0.050***	0.074**
	(0.003)	(0.005)	(0.007)	(0.013)	(0.010)	(0.009)	(0.015)	(0.029)
Dt1	0.078***	0.103***	0.078***	0.132***	0.012	0.000	0.037**	0.051*
	(0.003)	(0.006)	(0.007)	(0.014)	(0.011)	(0.011)	(0.017)	(0.031)
Dt2	0.064***	0.083***	0.057***	0.102***	0.007	0.015	0.023	0.040
	(0.003)	(0.006)	(0.007)	(0.014)	(0.011)	(0.011)	(0.017)	(0.031)
DBefore	0.090***	0.099***	0.075***	0.133***	-0.007	0.047***	0.033**	0.025
	(0.003)	(0.005)	(0.006)	(0.012)	(0.010)	(0.010)	(0.015)	(0.027)
R-squared	0.040	0.077	0.134	0.247	0.026	0.047	0.059	0.083
Obs.	84105	33889	21944	8148	9541	9822	4327	1318

Table A10: Effect of spikes on sales growth by Pavitt sector, firm-level fixed effects.

	France				**Italy**			
	Supplier Domin	Scale Inten	Specialized Suppl	Science Based	Supplier Domin	Scale Inten	Specialized Suppl	Science Based
Dt0	0.024***	0.033***	0.029***	0.054***	0.021**	0.025**	0.023	0.051*
	(0.003)	(0.005)	(0.007)	(0.012)	(0.010)	(0.010)	(0.017)	(0.030)
Dt1	-0.006**	0.003	-0.009	-0.022*	-0.007	0.000	-0.000	0.025
	(0.003)	(0.005)	(0.007)	(0.013)	(0.011)	(0.011)	(0.018)	(0.032)
Dt2	-0.010***	-0.005	-0.019**	-0.001	0.026**	0.003	-0.011	0.035
	(0.003)	(0.006)	(0.007)	(0.013)	(0.012)	(0.011)	(0.019)	(0.032)
DBefore	-0.016***	-0.015***	-0.014**	-0.023**	-0.010	0.012	0.001	0.031
	(0.003)	(0.005)	(0.006)	(0.011)	(0.010)	(0.010)	(0.017)	(0.028)
R-squared	0.017	0.019	0.017	0.030	0.015	0.011	0.028	0.033
Obs.	84105	33889	21943	8148	9513	9794	4298	1313

Table A11: Effect of spikes on employment by Pavitt sector, firm-level fixed effects.

	France				**Italy**			
	Supplier Domin	Scale Inten	Specialized Suppl	Science Based	Supplier Domin	Scale Inten	Specialized Suppl	Science Based
Dt0	0.062***	0.076***	0.079***	0.102***	0.023***	0.008	0.012	0.062***
	(0.003)	(0.004)	(0.005)	(0.009)	(0.006)	(0.007)	(0.009)	(0.022)
Dt1	0.064***	0.080***	0.069***	0.105***	0.028***	0.007	0.014	0.076***
	(0.003)	(0.004)	(0.005)	(0.010)	(0.007)	(0.007)	(0.010)	(0.023)
Dt2	0.053***	0.066***	0.048***	0.080***	0.009	0.016**	0.016	0.054**
	(0.003)	(0.004)	(0.005)	(0.010)	(0.007)	(0.008)	(0.010)	(0.023)
DBefore	0.076***	0.081***	0.067***	0.093***	0.005	0.022***	0.019**	0.013
	(0.002)	(0.004)	(0.004)	(0.008)	(0.007)	(0.007)	(0.009)	(0.021)
R-squared	0.026	0.035	0.032	0.082	0.022	0.015	0.008	0.053
Obs.	84106	33862	21945	8147	9944	10114	4412	1409

Table A12: Effect of spikes on employment growth by Pavitt sector, firm-level fixed effects.

	France				**Italy**			
	Supplier Domin	Scale Inten	Specialized Suppl	Science Based	Supplier Domin	Scale Inten	Specialized Suppl	Science Based
Dt0	0.033***	0.034***	0.032***	0.063***	0.029***	0.017***	0.026***	0.041**
	(0.002)	(0.004)	(0.004)	(0.008)	(0.005)	(0.006)	(0.008)	(0.016)
Dt1	0.005**	0.005	-0.001	-0.003	0.008	0.008	0.007	0.010
	(0.002)	(0.004)	(0.004)	(0.008)	(0.006)	(0.007)	(0.008)	(0.017)
Dt2	-0.005**	-0.007*	-0.016***	-0.003	-0.001	0.005	0.006	-0.005
	(0.003)	(0.004)	(0.004)	(0.008)	(0.006)	(0.007)	(0.009)	(0.017)
DBefore	-0.010***	-0.013***	-0.009**	-0.017**	-0.007	-0.002	-0.014*	-0.005
	(0.002)	(0.003)	(0.004)	(0.007)	(0.005)	(0.006)	(0.008)	(0.015)
R-squared	0.023	0.024	0.026	0.046	0.020	0.009	0.023	0.015
Obs.	84101	33845	21945	8145	9944	10114	4412	1409

Table A13: Effects of investment spikes and new plants opening productivity and prod. growth by Pavitt sector, firm-level fixed effects.

	Prod				Prod Gr			
	Supplier Domin	Scale Inten	Specialized Suppl	Science Based	Supplier Domin	Scale Inten	Specialized Suppl	Science Based
Dt0	0.008**	0.005	0.020***	0.019	-0.024***	-0.021***	-0.007	-0.011
	(0.004)	(0.007)	(0.008)	(0.016)	(0.004)	(0.008)	(0.009)	(0.018)
Dt1	0.012***	0.012*	0.019**	0.006	-0.001	0.003	0.009	-0.003
	(0.004)	(0.007)	(0.008)	(0.017)	(0.005)	(0.008)	(0.009)	(0.020)
Dt2	0.007*	0.008	0.015*	0.019	-0.008*	0.005	0.006	0.003
	(0.004)	(0.007)	(0.008)	(0.017)	(0.005)	(0.008)	(0.010)	(0.020)
DBefore	0.018***	0.027***	0.009	0.022	-0.002	0.002	0.000	0.004
	(0.003)	(0.006)	(0.007)	(0.014)	(0.004)	(0.007)	(0.008)	(0.016)
Dt0 Plant	-0.019*	0.031	-0.022	-0.042	-0.023*	0.047**	-0.039	-0.055
	(0.011)	(0.019)	(0.021)	(0.040)	(0.013)	(0.022)	(0.025)	(0.046)
Dt1 Plant	-0.035**	-0.034	-0.051*	-0.039	-0.014	-0.008	-0.048	0.027
	(0.014)	(0.024)	(0.027)	(0.050)	(0.017)	(0.028)	(0.032)	(0.058)
Dt2 Plant	-0.018	-0.026	-0.030	0.017	0.013	-0.003	0.006	-0.012
	(0.015)	(0.027)	(0.030)	(0.053)	(0.017)	(0.031)	(0.036)	(0.061)
R-squared	0.005	0.009	0.051	0.059	0.004	0.003	0.003	0.008
Obs.	69992	28239	18174	6635	69890	28172	18142	6618

Table A14: Effects of investment spikes and new plants opening on sales and sales growth by Pavitt sector, firm-level fixed effects.

	Sales				Sales Gr			
	Supplier Domin	Scale Inten	Specialized Suppl	Science Based	Supplier Domin	Scale Inten	Specialized Suppl	Science Based
Dt0	0.070***	0.088***	0.082***	0.142***	0.017***	0.030***	0.029***	0.040***
	(0.003)	(0.006)	(0.007)	(0.015)	(0.003)	(0.006)	(0.008)	(0.014)
Dt1	0.063***	0.084***	0.076***	0.107***	-0.006	0.006	-0.006	-0.026*
	(0.004)	(0.006)	(0.008)	(0.016)	(0.004)	(0.006)	(0.008)	(0.015)
Dt2	0.052***	0.075***	0.040***	0.086***	-0.009**	-0.002	-0.024***	-0.003
	(0.004)	(0.006)	(0.008)	(0.016)	(0.004)	(0.006)	(0.008)	(0.015)
DBefore	0.068***	0.078***	0.056***	0.104***	-0.013***	-0.010*	-0.006	-0.017
	(0.003)	(0.005)	(0.007)	(0.013)	(0.003)	(0.005)	(0.007)	(0.012)
Dt0 Plant	0.000	0.035**	0.019	-0.061*	0.012	0.027	0.001	-0.019
	(0.010)	(0.017)	(0.020)	(0.037)	(0.010)	(0.017)	(0.021)	(0.034)
Dt1 Plant	0.018	0.031	-0.024	-0.004	-0.010	-0.020	-0.035	0.027
	(0.013)	(0.022)	(0.026)	(0.046)	(0.013)	(0.022)	(0.027)	(0.043)
Dt2 Plant	0.002	-0.007	-0.059**	0.036	-0.019	-0.030	0.026	-0.007
	(0.014)	(0.024)	(0.030)	(0.049)	(0.014)	(0.024)	(0.031)	(0.045)
R-squared	0.027	0.060	0.105	0.188	0.011	0.014	0.011	0.026
Obs.	70246	28388	18229	6686	70246	28388	18228	6686

Table A15: Effects of investment spikes and new plants opening on employment and empl. growth by Pavitt sector, firm-level fixed effects.

	Empl				**Empl Gr**			
	Supplier Domin	Scale Inten	Specialized Suppl	Science Based	Supplier Domin	Scale Inten	Specialized Suppl	Science Based
Dt0	0.052***	0.060***	0.062***	0.100***	0.029***	0.030***	0.024***	0.057***
	(0.003)	(0.004)	(0.005)	(0.010)	(0.003)	(0.004)	(0.005)	(0.009)
Dt1	0.052***	0.065***	0.062***	0.091***	0.005*	0.005	-0.005	-0.004
	(0.003)	(0.005)	(0.005)	(0.011)	(0.003)	(0.004)	(0.005)	(0.009)
Dt2	0.043***	0.055***	0.034***	0.070***	-0.004	-0.005	-0.020***	-0.007
	(0.003)	(0.005)	(0.006)	(0.011)	(0.003)	(0.004)	(0.005)	(0.009)
DBefore	0.057***	0.063***	0.046***	0.069***	-0.005**	-0.010***	-0.010**	-0.015*
	(0.002)	(0.004)	(0.005)	(0.009)	(0.002)	(0.003)	(0.004)	(0.008)
Dt0 Plant	0.006	0.035***	0.013	-0.044*	0.014*	0.012	0.034***	0.002
	(0.008)	(0.013)	(0.014)	(0.025)	(0.008)	(0.012)	(0.013)	(0.022)
Dt1 Plant	0.015	0.025	-0.002	0.021	-0.004	-0.001	0.004	0.014
	(0.011)	(0.016)	(0.018)	(0.032)	(0.010)	(0.015)	(0.016)	(0.027)
Dt2 Plant	0.014	0.019	-0.043**	-0.013	0.004	0.012	0.008	-0.017
	(0.011)	(0.018)	(0.021)	(0.033)	(0.011)	(0.017)	(0.019)	(0.029)
R-squared	0.026	0.031	0.027	0.059	0.021	0.021	0.025	0.044
Obs.	70248	28366	18229	6686	70243	28353	18229	6685

Table A16: Determinants of firm level investment, robustness test with TFP

	France	**Italy**
Empl t-1	0.004***	0.015***
	(0.001)	(0.003)
RoS t-1	0.001	0.224***
	(0.001)	(0.033)
TFP t-1	0.032***	0.022***
	(0.002)	(0.005)
TFP Gr t-1	0.055***	0.168***
	(0.017)	(0.052)
Sales Gr t-1	-0.012	-0.121**
	(0.017)	(0.053)
Empl. Growth t-1	0.122***	0.170***
	(0.014)	(0.054)
Export t-1	-0.002	0.002
	(0.002)	(0.034)
D1	0.118***	0.121***
	(0.003)	(0.008)
D2	0.060***	0.075***
	(0.003)	(0.008)
D3	0.045***	0.054***
	(0.003)	(0.010)
Year dummies	Yes	Yes
Sector dummies	Yes	Yes
Observations	115725	18734
Brier score	0.1078	0.1327

Notes: Table reports random effects logistic regression of noted firm characteristics on the probability to observe an investment spike. Marginal effects at means are reported, standard errors in parentheses. Spike measure: Kernel rule. Asterisks denote significance levels (***: p <1%; **: p<% 5%; *: p<10%).

Table A17: Effect of spikes, robustness test with TFP

	France				**Italy**	
	TFP		TFP Gr.		TFP	TFP Gr.
Dt0	0.042***	0.038***	-0.003	-0.005*	0.028***	0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.006)	(0.007)
Dt1	0.016***	0.012***	-0.030***	-0.028***		
	(0.002)	(0.002)	(0.002)	(0.003)	-0.009	-0.026***
Dt2	0.012***	0.010***	-0.003	-0.004	(0.006)	(0.008)
	(0.002)	(0.002)	(0.002)	(0.003)	-0.001	0.009
DBefore	0.013***	0.009***	-0.006***	-0.005**	0.005	0.011
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.007)
DPlant t0		-0.003		-0.003		
		(0.007)		(0.008)		
DPlant t1		0.004		-0.011		
		(0.009)		(0.010)		
DPlant t2		-0.007		-0.015		
		(0.009)		(0.011)		
R-squared	0.121	0.122	0.012	0.013	0.130	0.014
Obs.	132029	110183	132008	110167	25871	25865

Notes. Table reports results of regression (fixed effects) for the impact of investment timing on firm performance. Spike measure: Kernel rule. Standard errors in parentheses. Asterisks denote significance levels(*: p<0.10, **: p<0.0, ***: p<0.01)